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A swarm intelligence based approach to the mine detection problem

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**A SWARM INTELLIGENCE BASED APPROACH TO THE MINE DETECTION
PROBLEM**

By

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Thesis submitted to the Faculty of Rochester Institute of Technology in partial
fulfillment of the requirements for the degree of

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Author

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- [2] Vignesh Kumar M, Ferat Sahin, “Foraging in Ant Colonies applied to the Mine Detection Problem”, IEEE International Workshop on Soft Computing in Industrial Applications, 2003

- [3] Vignesh Kumar M, Ferat Sahin, “Cognitive Maps in Swarm Robots for the Mine Detection Application”, IEEE International Conf. Systems, Man and Cybernetics, 2003

- [4] Vignesh Kumar and Ferat Sahin, “Ant Colony Optimization based Swarms: Implementation for the Mine Detection Application” IEEE International Conf. Systems, Man and Cybernetics, 2004

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Abstract

This research focuses on the application of swarm intelligence to the problem of mine detection. Swarm Intelligence concepts have captivated the interests of researchers mainly in collective robotics, optimization problems (traveling salesman problem (TSP), quadratic assignment problem, graph coloring etc.), and communication networks (routing) etc [1]. In the mine detection problem we are faced with sub problems such as searching for the mines over the minefield, defusing them effectively, and assuring that the field is clear of mines within the least possible time. In the problem, we assume that the mines can be diffused by the collective action of the robots for which a model based on ant colonies is given. In the first part of the project we study the ant colony system applied to the mine detection problem. The theoretical aspects such as the ant's behavior (reaction of the ants to various circumstances that it faces), their motion over the minefield, and their process of defusing the mines are investigated. In the second section we highlight a certain formulation that the ants may be given for doing the task effectively. The ants do the task effectively when they are able to assure that the minefield is clear of the mines within the least possible time. A compilation of the results obtained by the various studies is tabulated. In the third and final section we talk about our emulations conducted on the Multi Agent Biorobotics Lab-built groundscout robots, which were used for the demonstration of our swarm intelligence-based algorithms at a practical basis. The various projects thus far conducted were a part of the Multi Agent Biorobotics Lab at Rochester Institute of Technology.

1. Introduction

Intelligence lies in the judicious use of smartness (a collection of knowledge) of an entity or a group of entities. Animals, humans and robots can be analyzed as multi tasking autonomous control systems based on well-established ethological principles that exhibit intelligence. Biological systems are argued to exhibit a better understanding of intelligence than that of traditional ‘artificial intelligence’ [1, 2, 3, 6]. Applications to biological based systems are constantly expanding. One of the interesting aspects of biological based studies is swarm intelligence. Swarm intelligence refers to the studies wherein intelligence is bestowed in a disembodied medium. Swarm Intelligence can be defined as the property by which a group of simple, autonomous, intelligent agents interacting indirectly and collectively bring about solutions to complex tasks [1, 2, 7, 8]. The tasks are usually distributive in nature. Basically swarms exhibit models of behavior-based systems, which are autonomous (no central control involved), and have a strong desire for reaction and adaptability. Robustness in problem solving is achieved with simple individuals interacting in a dynamic environment producing complex tasks. In this project we applied the principles of swarm intelligence to the problem of mine detection. Examples of swarms include ant colonies, wasps, birds, cattle herds, frogs and other colony based living organisms. We report the parameters assumed, observations made and results obtained in this application.

The first section of the review explains the basic attributes of swarm intelligence, with regard to the ant colony, which is typical of the swarm family. We review the general organization of the ant colony system and its exhibition of tasks in response to the routine problems that it faces. Some of the concepts are ant foraging, division of labor, task allocation, and collective transportation of food. Some of the major properties (stigmergy, emergent behavior and collective adaptation) by which the ant colony works are also discussed. In Section 3 we discuss our main application, ‘the mine detection problem’. Section 4 provides the problem definition, the assumptions made, and the strategies utilized in solving the problem using a multi agent system-based ant colony model. Section 5 focuses on the design of our implementation of the mine detection algorithm at a practical level using groundscout robots.

2. Background and Motivation

2.1 Multi Agent Systems

Intelligent Agents are integrated systems that incorporate major capabilities drawn from several research areas: Artificial Intelligence, Databases, Programming Languages, and Theory of Computing. A new trend in Distributed Artificial Intelligence (DAI) considers software agents as intelligent units that may be customized and composed with other similar units to build complex systems [1]. The corresponding agent model is an abstraction that corresponds to functional aspects of real entities more directly than to blocks of executable information and extends the traditional object model in several ways [1, 8]. In artificial intelligence research, agent-based systems technology has been hailed as a new paradigm for conceptualizing, designing, and implementing non-linear and complex systems. Agents, like objects, have an internal state, which reflects their knowledge. However, this knowledge may be based on default assumptions or partially specified and refined during an agent's lifetime. Agents are sophisticated entities that act autonomously yet collectively, across open and distributed environments, to solve a growing number of complex problems [1, 8, 9, 10, 11]. Multi agent systems distribute computational resources and capabilities across a network of interconnected agents. Agents show an external behavior consisting of communicative acts to other agents or control actions on software or hardware devices. Agents can communicate with one

another through standard agent-independent communication languages such as KQML, ACL, and FIPA [3].

A centralized system may be plagued by resource limitations, performance bottlenecks, or critical failures; a Multi Agent System is decentralized and thus does not suffer from the 'single point of failure' problem associated with centralized systems [4, 5]. Multi Agent Systems model problems in terms of autonomous interacting component-agents, which are proving to be a more natural way of representing task allocation, team planning, user preferences, open environments, and so on. These systems efficiently retrieve, filter, and globally coordinate information from sources that are spatially distributed. A Multi Agent System allows for the interconnection and interoperation of multiple existing legacy systems. By building an agent wrapper around such a system, they can be incorporated into an agent society [4, 5]. Multi Agent Systems enhance overall system performance, specifically along the dimensions of computational efficiency, reliability, extensibility, robustness, maintainability, responsiveness, flexibility, and reuse [1].

From the distributed artificial intelligence point of view, most complex software systems and applications are conceived as organizations of cooperative agents. Agents can be part of a stand-alone application or be distributed over a network. Interactions among agents are established dynamically according to the dependencies among their capabilities. A single function may be provided by different agents and a single agent

may provide several functions. Agents can cooperate since they share the same communication language and a common vocabulary, which contains words appropriate to common application areas and whose meaning is defined in a shared ontology [3]. Multi Agent-based systems composed of simple agents that demonstrate complex collective behavior offer several advantages over traditional Artificial Intelligence (AI). Traditional Artificial Intelligence proposes for embedding all functionalities of intelligence into a single entity. This makes the design process highly complex and the output highly unstable for high-end applications. Though some problems are best suited for knowledgeable and able agents, they have significant shortcomings in at least one of the following areas: robustness, adaptability, stability, and scalability. Complex agents may fail, and if a central controller is involved in directing actions of agents, it has to be able to recover in the event of agent failure. Systems in which agents change their strategies in response to actions by other agents can quickly adapt to environmental changes; however, this feature is usually achieved at the expense of global stability [4, 5]. The high communication and computational cost required to coordinate agent behavior constrain the size of the traditional Artificial Intelligence to at most a few dozen agents. Yet another disadvantage is that the complexity of the agent's internal states and its interactions with other agents make these systems ill suited for rigorous quantitative analysis. A well-designed Multi Agent System on the other hand, is an efficient, robust, adaptive and stable agent-based system. It lacks central control, meaning that the system can recover quickly from mistakes, agent failure and environmental change. Because it has very low communication and computational requirements, there are virtually no

constraints on system size. This simplicity makes Multi Agent System amenable to mathematical analysis. Despite their numerous advantages, there have been relatively few implementations of Multi Agent System outside of distributed robotics. The scarcity is partially explained by the difficulty of designing a Multi Agent System. The designer, in a sense, has to reverse-engineer the problem, i.e., determine what microscopic interactions, or basis behaviors, are necessary to produce the desired collective behavior [4, 5].

A set of basis behaviors defined for an entity concludes itself to produce complex behavioral patterns. These are the fundamental basis as defined in behavior-based agent modeling [1, 2]. For example we present here an example that we intent to use later in our robot development model. A small set of primitive behaviors such as collision avoidance, trail following, dispersion, aggregation and homing (mostly seen in ant colonies) is sufficient to synthesize complex behavior, such as foraging and flocking, in a single robot or a group of robots. We claim that a similar set of primitive agent strategies can be formulated for agents, and they will serve as basic components for synthesizing collective behavior. Consider, for example, coalition formation. Coalition formation is a desirable behavior in systems where a group of agents can accomplish a task more effectively than a single agent can. The tasks may be very different ranging from collective block pushing, to commuter ride sharing, to consumers forming buying clubs to purchase products in bulk in order to save money. Yet the underlying fundamental mechanism is the same for each application. We will demonstrate that coalition-

formation in a system of agents can result from two primitive agent strategies: *dispersion* or foraging and *aggregation* or recruitment [1, 5, 6, 8]. Dispersion allows the agents to explore the environment in which they are situated and to encounter other agents and coalitions. Once an agent encounters a coalition or arrives at a point of interest, it makes a decision about whether to join it (aggregate). Other collective behaviors, such as distributed control and optimization (e.g., task allocation), distributed resource management (e.g., load balancing), collaborative information gathering, and cooperative transport in robots, may require the introduction of other primitive strategies. Figure 1 shows a representation of the basic qualities that multi agents are embellished with in any work environment.

2.2. Social Insects

It has been recognized in physics and biology that complicated global activity can result from very simple local interactions [1, 2]. Examples of this phenomenon pervade the natural world and include among others: pattern formation in thermal convection, Turing patterns in chemical reaction-diffusion systems, and the transition by which single cell slime mold amoeba aggregate to form a functioning multi-cellular organism. Collective behavior emerging from local microscopic interactions has also been observed in many species of social insects [11, 12, 16, 17]. Though individual insects are simple creatures, having limited memory, and a knowledge or reasoning facility, an insect society demonstrates complex behaviors. Hives, ant trails and swarms are examples of such

robust, adaptable, and seemingly organized collective behaviors that do not have any central control.

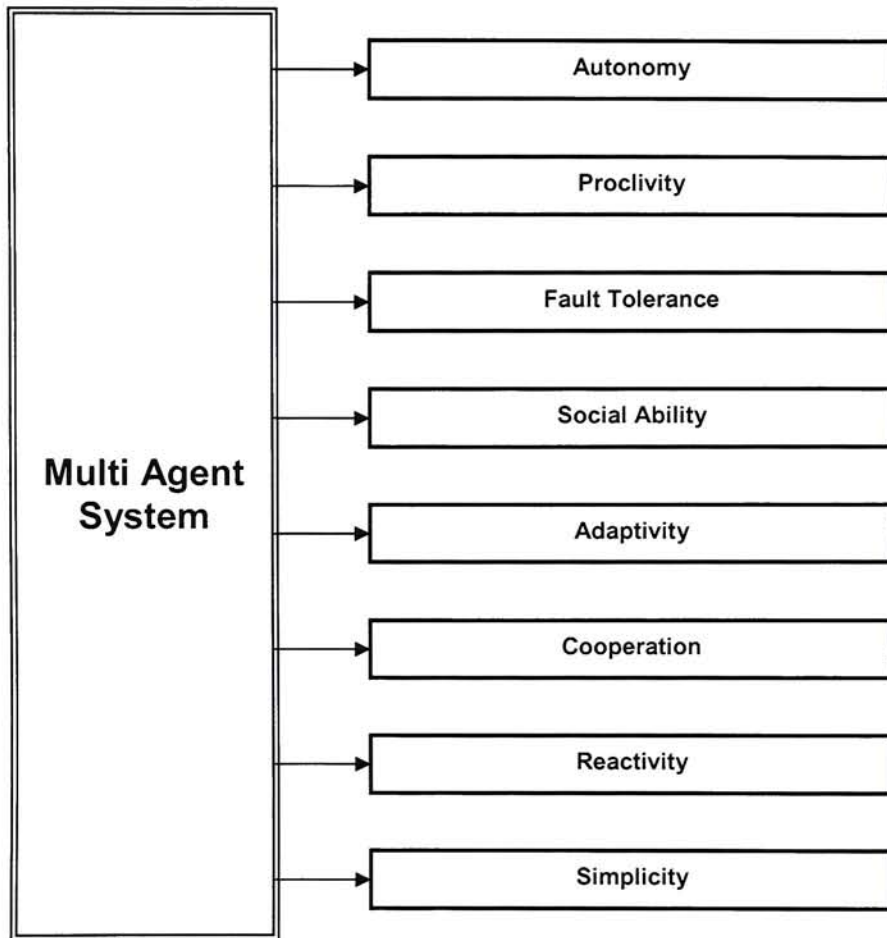


Figure 1: Qualities of Multi Agent Systems [4, 5]

Social insects are a class of swarms that exhibit collective living and task execution. A challenging question in collective robotics is how behaviors from large systems can be derived from simple interacting components. Social insects in nature exhibit collective

behaviors in maintaining the basic necessities of their societies. Several researchers have proposed models based on social insects for the control of interacting agents [1, 4, 7, 8, 9, 10]. Ants, bees, and wasps form the most researched topics in the study of social insects. Both ants and bees have limited capabilities. Some of them are their reaction to light, smell, and sound. They have the ability to react to situations that are dictated by the environment, ability to secrete chemicals that spread over the environment. Yet they are able to perform complex tasks such as nest building and prey retrieval collectively. The forces that influence an individual during their performance of a task are dynamically balanced. Deneubourg suggests that the ability of the individuals to execute its task is a combination of concepts like positive feedback and stigmergy [1, 2]. The individuals in a swarm environment can be viewed as agents interacting in a multi-agent system. Most of the features that an agent has such as autonomy, adaptiveness, proactivity and reactivity, ability to communicate directly or indirectly are found in the individuals of a swarm system.

One mechanism to achieve collective task execution is to have a *common goal* for all the individuals involved in the execution of the task. Weaver ants (leaf cutters) exhibit such characteristics while performing the corpse removal function. Secondly, a behavior defined by *following* can be used to model collective task execution [1, 2, 11, 12, 13]. Pheromone trails in ants, odor trails and scents are physical entities that can be used by groups to convey information for other individuals to follow. Such an exhibition of achieving collective behavior can be seen in ants and honeybees. *Environmental cues*

can be another factor that may be utilized to elicit collective behavior [1, 2, 9, 10]. Visual cues by which ants are able to orient themselves along their path come under this category. Many researchers propose a *response-threshold* model for defining how actions begin inside a colony [1, 16, 17]. When individuals of a colony (ant colonies) detect fellow mates involved in a particular action (work), they respond to the work with a stimulus which is a direct function of the number of individuals involved and the rate of completion of the task. In the following section we focus on the ant colony, which is a rigid member of the swarm family. Three distinct behavioral phenomena are seen in insect societies: Self Organization, Emergent behavior, and Stigmergy

2.2.1 Self-Organization

Self-organization is an attribute of a system to respond to its own organizational abilities without the intervention of external forces. *Evolution* is the process, which initiates the mechanisms of self-organization. Theories of evolution pose that self-organization arises out of the processes of natural selection [1, 5]. Generally they arise out of noise and random fluctuations that naturally arise out of the system. Non-linear properties accompany the concept of self-organization. Positive and negative feedback mechanisms are exhibited in self-organization. Positive feedback systems are those systems where the output (the response of the system) adds on to the input through a feedback mechanism. The output of positive feedback system normally explodes in time. Negative feedback mechanisms can counter the destructive effects of positive feedback. In negative

feedback the feedback component is subtracted from the input, which is fed to the system. The interaction of positive and negative mechanism stabilizes the system.

Self-organization has three main characteristics. First, a self-organizing system can accomplish complex tasks with little and simple individual behaviors. Secondly, a change in the environment may influence the system to generate a different task, without any change in the behavioral characteristics. Finally, any small differences in individual behavior can influence the collective behavior of the system. Therefore, social complexity of the system is compatible with simple and identical individuals, as long as communication among the members can provide the necessary amplifying mechanism. The major advantage with self-organization is that the individuals can be programmed in a simple manner and the amount of individual-to-individual communication also need not be complex. Such a simple system will have adaptive characters, which can be apt for solving complex tasks. When deterministic systems are considered against self-organizing systems, it occurs always that the amount of hardware and software complexity that the deterministic system may have increases with the complexity of the problem while the hardware and software complexity for a self-organizing system remains manageable in most cases. Homogeneity and simplicity of the individuals of the self-organizing system helps in the reduction of manufacturing costs. Unlike the case of deterministic systems, the failure of one of the individuals in the self-organizing system does not affect the working of the system as a whole. Examples of self-organization that

can be found naturally are colonies of wasps and ants, schools of fish, flocks of birds, and termites [10, 16, 17].

2.2.2 Emergent Behavior

Emergent behavior is a natural behavior exhibited by swarms in nature. Emergent behavior is a natural offshoot of multiple interactions. Multiple interactions occur when a group of agents that has been defined with a set of basic, simple rules interact among themselves to produce complex patterns to emerge [1, 2, 5]. In swarms the action of one individual affects the action and responses in the colony. These interactions seen among the individuals of the colony manifest itself at the colony level to solve the global problem present in front of the colony. An interesting factor observed is that though at the colony level they seem to be organized, they exhibit stochastic or random behaviors at the individual level. Such an observation is called *Emergent Behavior* [1]. The role of the agents involved in the problem solving process is essentially seen as how the role of one individual affects the others and how the problem solving process is distributed among the diverse agents. Emergent behavior emerges from interactions of the components local to the system. This behavior can be both beneficial and detrimental to the system in solving its problem. Both positive feedback that produces amplification and negative feedback that inhibits the output thereby controlling it are generally offshoots of emergent behavior.

Emergent behavior can take different forms. Sometimes the system will be attracted to a fixed and stable point, which may or may not correspond to the behavior intended by the designer of the system. Sometimes it may produce oscillations. Sometimes it may enter a formally chaotic regime, which superficially looks more like random and the system getting unbounded. Chaotic behavior of a system results when the reaction of the system behavior with respect to initial conditions. This latter case is particularly important. A system that behaves randomly because of noise in the environment can often be corrected by improved quality control, but these methods will not improve formally chaotic behavior (the unbounded nature of the output) that emerges in a distributed system. In this case, the solution lies in structural modification or parameter tuning, not tighter control over varying environmental conditions [10, 11].

2.2.3 Stigmergy

Any system involving collective agents needs to have direct or indirect communication between the individual agents. One form of communication that is seen in swarms is a modification of the environment to highlight their present responses for the others to follow and act accordingly. Such indirect communications among the individuals in the collective system are referred to as stigmergy [1, 2, 9, 10]. Stigmergy can be seen as a mediator for animal-to-animal interaction. When the individuals in a colony do not differentiate between their own actions with that of the others, direct communication between them becomes redundant. Swarms use a type of communication, which prevails indirectly, within the individuals of the group. A modification in the environment by an

individual can act as a beacon for the others in the colony to follow. By this any individual can impose its reactions to the others and expect them to use it as a means to modify the environment fruitfully towards the global goal. This sort of 'expectation' of individuals from each other can be used by the colony as a whole to bring about the final solution to the problem in hand. The outcome of the expectations of individuals can be positive or negative or relative to which the individual acts in response. An accumulation of 'expectations' and 'outcomes' generally given in response to local problems grows collectively to solve the global problem [1]. One of the interesting factors, which can be observed in swarm intelligence, is 'random fluctuations'. Fluctuations arise when an individual or a group of individual responds to the environment not in a way expected by the rest of the individuals. These fluctuations can be seeds for newer routes and practices for the colony, which may lead to the optimal solution. In the following section we analyze how an ant colony organizes itself with the qualities mentioned above.

2.3 The Ant Colony System

Ants belong to the insect order Hymenoptera and are close relatives of bees and wasps. The average life expectancy of an ant is 45-60 days. Like all insects, ants have six legs. Each leg has three joints. The legs of the ant are very strong so they can run very quickly. If a man could run as fast for his size as an ant can, he could run as fast as a racehorse. Ants can lift 20 times their own body weight. An ant brain has about 250 000 brain cells. A human brain has 100 million cells so a colony of 40 000 ants has collectively the same size brain as a human. The abdomen of the ant contains two

stomachs. One stomach holds the food for itself and second stomach is for food to be shared with other ants. Like all insects, the outside of their body is covered with a hard armor this is called the exoskeleton. Ants have four distinct growing stages, the egg, larva, pupa and the adult. Biologists classify ants as a special group of wasps (*Hymenoptera Formicidae*). There are over 10000 known species of ants.

A major branch of Swarm Intelligence is the study of Ant Colonies. Ant Colonies are well-coordinated and well-organized entities that show a bottom to top approach without a rigid hierarchy [1, 2]. Individual manifestations of stimuli and responses are in response to local problems, which grow collaterally to solve the complex global problem. The major feature of the ant colony system is the absence of central control. All of the ants are assumed to have absolutely no or very less means of direct communication among themselves, yet they have the responsibility of carrying out the routine tasks of the colony system. Various ant models have been proposed by researchers, of which the prominent are from Deneubourg et al., Gross et al [1, 2, 3, 4]. Deneubourg's model emphasizes that positive feedback obtained by individuals reinforces the ability of the ants to interact at the colony's hierarchical levels [1, 2]. Positive feedback is the imposition of popular actions performed by agents, which is caused by the performance of the action itself. Positive feedback often results in chaos, which are countered by negative feedbacks. A dynamic system becomes successful when there is a balance of forces resulting from positive and negative feedbacks. In the following discussion we shall look at certain characteristics of ant colonies, which exhibit collective intelligence.

Another important and interesting feature of the ant colony is amplification of fluctuations. Positive feedback acts as an important component in amplifying the noise like random fluctuations inherently present in the system (mostly produced without a source, as in the case of oscillators) to produce varied and newer properties for exploration that could enhance the overall performance of the system [4, 5]. In the following section we discuss certain features of the ant colony that we will be using for building the model for the mine detection application.

Ant algorithms are multi-agent systems in which the behavior of each single agent, called artificial ant or ant for short in the following, is inspired by the behavior of real ants [1, 10]. Ant algorithms are one of the most successful examples of swarm intelligence systems, and have been applied to many types of problems, ranging from the classical traveling salesman problem to routing in telecommunications networks [1]. In Section 3, we will focus on the ant colony optimization (ACO) meta-heuristic algorithms, which define a particular class of ant algorithms in its own [1, 5, 10].

2.4 Navigation in Ants

Navigation in ants is a task involving coordination of nestmates. The basic means of communication during navigation among the individuals of an ant colony is by the laying of pheromone trails. Pheromones are special chemical substances secreted by the ant during their motion so as to convey information that it has followed a particular route. Pheromone concentration has the ability to decay (evaporate) in time. Ants tend to

follow routes rich in pheromone concentration. This aspect of ant motion was investigated by researchers in most ant species and has been applied to several optimization problems [1, 9, 10, 15]. The famous traveling salesman problem (TSP) and the quadratic assignment problem are examples where pheromone trails of ants are used [13, 14]. Routing in communication systems is another important and interesting application where ant based optimization algorithms has been successfully applied.

Though much of literature regarding ant navigation has a pheromone-base, other means of ant navigation methods also exist in literature. The use of *Cognitive or Visual Cues* (terrain and celestial cues) by ants during navigation has been reported in *Polyrhachis laboriosa* or tree dwelling ants [11, 12, 13]. In this type of motion, the visual cues act as means for the individuals to evaluate their position with respect to certain known coordinates (usually the nests). This can be done in two ways: path integration and the ability of the ants to remember their positions during motion [14, 15]. In our application, we have applied such type of foraging behavior to the ants, which obviates the use of pheromones for their motion.

Navigation in ants is normally a collective activity. Two main modes of navigation are observed in ant colonies. In the first mode a certain chemical called pheromone is secreted all along the path an ant travels. These pheromones act as beacons for followers or others to decipher their future enroute. Ants gather their nestmate's pheromone trail information to devise their future foraging or navigational strategy. Certain ants, as they

return to the nest with food, lay down a trail pheromone. This trail attracts and guides other ants to the food source. It is continually renewed as long as the food holds out. When the supply begins to dwindle, trail making ceases. The trail pheromone evaporates quickly so other ants stop coming to the site and are not confused by old trails when food is found elsewhere. The property of pheromone evaporation thus acts as a mechanism to weed out redundancy in the systems and preserves its robustness and dynamism. Other ants will not maintain the trail unless food is placed at its end. In the second mode, an organizational map of visual cues or visual information is collected during foraging, which may be utilized to embark on future routes. Mostly this method is used when ants carry food particles to their nests.

Any point in space can be specified by its location from an *infinite* number of other points. As a consequence, there are numerous choices open to an ant when attempting to remember the location of a goal. Constraining the choices of ants are physical properties of the natural environment. For example, short landmarks will tend to become obscured by intervening objects, so we expect that ants will tend not to remember them, and under some circumstances we would not expect the ants to remember moving landmarks [12, 13, 14, 15]. Another factor that would limit the total amount of spatial information that can be remembered is that the amount of memory that ants have at any point of time is finite. For this reason, there are likely to be trade-offs between the number of landmarks used to remember the location of each goal, the accuracy with which each goal is remembered and the number of goals that can be remembered. Clearly then, as an ant

moves around in its environment, it is faced with numerous decisions about the type of spatial information to remember. Two processes can be distinguished. The first involves decisions about the types of landmarks to remember. The second concerns the geometrical properties of space that are specified by the remembered landmarks [14, 15].

2.5 Collective Transportation in Ants

Collective transport is a complex phenomenon in insect colonies that involves detection and physical transportation of objects (mainly food particles, brood, etc.). Collective transportation not only involves these basic concepts, but also becomes complicated when features like coordination in collective movement and stagnation recovery are involved. One of the main aspects of the collective transportation is the study of cooperative prey retrieval in ants. Cooperative prey retrieval is the act of finding the prey, deciding on how it can be transported to the destination (nest) and the physical transportation of it to the nest. This phenomenon involves several aspects:

- How does an ant know that the object is too heavy for it to lift alone, and has to recruit nest-mates to start collective transportation?
- How is it able to attract nest-mates when help is needed?
- How do they come to know about the right number of ants to start collective transportation?
- How do they cooperate and coordinate among themselves in the actual transportation process and how to tackle any obstacles in the path?

The process of transportation begins with the detection of the prey by a single or a small group of ants. At this point a decision has to be made as to whether the object can be lifted or pulled by the detector alone or whether some more of the nestmates have to assist in it. In most cases the main factor, which leads to group transportation, is the weight of the prey. A solitary ant initially tries to realign itself and the prey to test for solitary transportation. In cases when this turns out to be futile group transportation is needed. Other factors that can lead to group transportation are the prey's resistance to motion and the preference of the prey. In *Pheidole pallidula*, it was observed that it was the resistance to traction rather than the weight of the prey itself that was responsible to invoking group transportation [1]. We can thus see that it is the manifestation or accumulation of individual's inability in execution of the task that is responsible for group's responsive patterns towards the task change.

2.6 Recruitment of Nestmates

Recruitment of nestmates is the process of attracting nestmates when an ant succeeds in detecting a prey and after certain attempts realizes that solitary transportation is not possible. Holldobler showed that in the species of *Novomessor* (*Novomessor albisetosis* and *Novomessor cockerelli*) two distinctive processes were involved in the process of recruiting [1, 2]. In the first process the ant, which detects the prey, spreads a scent around the prey, which attract the ants present in the local vicinity of the prey. This is called short-range recruitment (SRR) [1]. In most cases the concentration of the secretion decreases spatially. It was also observed that as time progresses the number of ants

following the scent decreases, which may be due to the scent getting evaporated or to allow for some other effective techniques to be followed by the ants at the prey so that collective transportation is possible. SRR is followed by long-range recruitment (LRR), a process wherein the ant, from the point of the scent to the nest, lays a pheromone trail so that other ants may follow to assist in collective transportation [1]. It was shown by Holldobler that LRR is resorted to only when the inability of the group of ants in moving the prey cumulates over time.

The behavior as to how an ant resorts to attracting other ants around it or in the ant colony gives us important cues in how coordination in a collective system can be achieved. The important point to be noted here is that there is no physical communication involved in this process. The basic phenomenon of producing changes in the environment, which acts as a beacon for the others to follow, is exhibit as here. As mentioned in Section 2.2.3, this phenomenon is generally referred to as stigmergy. The scent acts as the component of stigmergy in the case of SRR while the pheromone trail does this part in the case of LRR. This kind of behavior is also noted in the case of defense strategies in an ant colony system. Whenever one or a group of ants in the colony finds an imminent foreigner they resort to scent spreading as a means to attract others in the colony. In this case the time allocated for SRR is very short when compared to the case of prey retrieval. The basic aim of the coordination mechanism is to bring the optimal number of ants to the point of action. We may see the scent concentration decreasing as more and more ants are recruited for action. Mainly the number of ants required is decided on the size of the pray to be retrieved. As the concentration of the

scent decreases one can see that the tendency of the ants reacting towards SRR is reduced [1, 11, 14, 15].

2.7 Coordination in Collective Transportation

Coordination in the movement of ants is the ability of the ants involved in the transportation of the prey to bring about the right orientation of itself with respect to others both in time and space. The phenomenon of stigmergy is well exhibited in this case as the individual ants able to coordinate with the group with their bodily tactile senses. Coordination is brought about by different species in different ways and is a subject, which is not well understood and has never been modeled. Another aspect involved in this is that of recovery from stagnation. Stagnation can occur when the workers with forces that are oriented in a manner canceling each other pull the prey and the effective force acting on it is either null or random. It suddenly becomes successful in the due course of time. This happens when the orientation randomly becomes cumulative in the right direction. Deneubourg defines this as the transition in phase [1, 3]. Most of the intricacies involved in attained coordination are not well-understood and no reliable model exists in these cases.

3. Swarm Intelligence based Approach for Mine Detection

3.1 Problem Definition

By the mine detection problem, we mean the problem of detecting and demining randomly placed mines over a field. We assume that the agents, which are deployed to demine the mines, are equipped with the ability to detect the mine when they approach them physically. The demining of the mines demands the collective action of a certain number of agents. The agents are simple and not communicative. The main goal of the work is to eliminate the central intelligence in driving the act for the completion of the task. Furthermore research is carried out in applying theories based on ant colony navigation to enhance performance results in terms of least possible time spent in action and assuring total coverage and clearance of the minefield. The minefield is assumed to be rectangular carrying randomly placed mines distributed uniformly. The agents are assumed to independent of its actions and not controlled by a central monitoring authority. Agents are equipped to bear actions on the environment that can elicit mass or group responses, which are favorable. One such action can be a scent spread around the mine, which can attract other agents. It is assumed that the collective action of a number of agents can defuse the mine. In our simulations it was assumed to be four and is constraint for all the mines. The mines are assumed to be of the same type demanding the same number of agents to demine them. In the next section we analyze the present and conventional technologies that are utilized to demine mines over a minefield.

3.2 Demining: Challenges and Trends

The standard set for humanitarian demining is 99.6 percent guaranteed clearance by the ‘Humanitarian Demining Development Programme’ [22]. A growing concern for international peace and stability is the use of mines both in war and defense. Traditional or classical techniques of control engineering were primarily used for the technologies involved in this area, but recently due to the boom in distributed control, a trend exists advocating the use of independent agents (usually multi-agents) in demining. The adaptation of a particular trend in the field of demining has not been easy. Much scrutiny would be done in deciding to adopt a particular technology, because of the sensitivity of the whole issue.

The number of people killed by land mines is ever increasing. More people die or get maimed from land mines than inter continental (ballistic) or nuclear weapons. In fact, there seems to be more concrete international conventions and laws on ballistic and nuclear arms than land mines. One of the most lucrative weapons for war or terrorism is land mines, because of their low cost and easy deployment. Most often a single land mine costs less than ten dollars, which is a very low price in the international market. The deployment also does not take a lot of effort or manpower. Figures state that on average as many as 110 million remain planted in ground on every continent, with more than eighty percent of these found on Asia and Africa alone [18, 20, 27]. It is estimated that at the present pace of clearing mines another thousand years would be consumed in demining them completely if no more are planted in this period. Every day about on

average 70 people are directly killed or maimed due to land mines [18]. The placement of land mines is normally at difficult terrains. Mainly hilly regions, mountain slopes, river beds, forests are chosen for their placement, which makes it all the more difficult to remove. Eighty percent of the mine removal process directly involves humans, which results in greater casualties of life. Because the land mines are normally found in third world countries, availability of funds for such a cause becomes the reason for involving humans in mine detection and removal.

Mines can be practically made out of any substance [18, 25]. Normally, they are stuffed with materials like metal, wood, plastic etc. A rusted mine is normally more dangerous than a fresh mine, due to its sensitivity and instability. More often it is seen that (in pressure sensed mines) lesser pressure causes the mines to explode, when rusted, than it would have required when it was fresher. Generally there are many specifications that may be used to classify mines, the most common being that of the company that manufactures them. Mines can be classified ranging very broadly, characterized by detonation range, type of sensors used, type of explosives used etc. The problem has a lot of financial constraints because large industry representatives have admitted that it is not financially profitable for them to invest in developing or producing low-end (or low-price) demining equipment. Industry is enticed by multimillion-dollar contracts, and governments simply are not putting that kind of money into demining technology contracts, either for high-tech or low-tech solutions. The military objective of many countries hinders humanitarian demining. Mine detection mission are politically

motivated and countries usually go for demining with military advanced in mind. This strategy is a reason for incomplete demining over many minefields. Many countries because of cost and time constraints adopt this approach.

3.3 Normal classification of mines

- **Anti-Personal Mines:** - Anti-personal mines are normally smaller when compared to the normal mines. They normally weigh around 200 grams and are usually 10cms in diameter. They are mainly targeted for a single person or a small group. They may be activated by pressure or trip-wires. Pressure activated types have a pressure gauge for sensing pressure while the trip wire activated ones may have small thread like wires running across fields which when stumbled on develops tension which may act as the triggering mechanism [20, 22].
- **Blast Mines:** - These are a category of anti-personal mines. These are the mines that are triggered by pressure, normally that of humans. When a person treads his foot on the sensors of this type of mine, a pressure gauge is activated and the mine is triggered. They may contain a small amount of explosives, which may be blast when activated. The explosion may lead to amputation, secondary mayhem or death. It is mostly deployed in Afghanistan, Cambodia, Iraq, Iran, Nicaragua, Angola, Mozambique and many other countries [20, 22].

- **Fragmentation Mines:** - These also belong to the category of anti personal mines. In this type metal fragments may be projected with high velocity into the surroundings, which may cause physical maim to the person in the vicinity. They also have the same triggering mechanisms that are used in anti personal mines. A typical example mine of this category is the Claymore mine (Directional fragmentation Mines) [20, 22].
- **Anti-Tank or Anti-Vehicle Mines:** - These are generally bigger mines and are more powerful. They are mainly targeted for war tanks and heavy vehicles. Usually they contain about 10 to 15 kilograms of explosives and have pressure gauges for sensors [20, 22].
- **Butterfly Mines:** - Millions of these small green mines can be scattered from helicopters or launched from artillery throughout the war. One 'wing' contains liquid explosive. When pressure is applied the explosive is forced into contact with the fuse. The amount of explosive is small, but it can still take a person's hand off [20, 22].

The explosive used in mines are mainly phosphorous containing compounds. Usually chemicals like Tri-nitro-toluene (TNT), RDX, tetryl, PETN are used [20]. Most of the

mine detection methods rely on odors released by the chemicals for detection. Since in a minefield the concentration of the odors may depend on a lot of factors such as wind direction, concentration of the mines deployed, the rate of false alarms that could be caused by this method is quite high [22].

The process of mine placement does not involve skilled work. Mines can be easily placed in trenches just deep enough as the length of the mine. The important point is that the cost involved in the process of buying and deploying a mine is much less compared to the cost involved in its removal. Aircrafts, submarines, surface ships, underwater robots and frogmen, as well as merchant ships, fishing ships, ferries and motorboats can place mines. A new trend seen is sea-mines, which are mines placed in seas or water logged areas. Some of the common sea mines are bottom mines, self-propelled mines and moored mines. A notable feature to be observed in the case of sea mines is that the mines can be physically moving (drifting mines) which may cause damages to ships and under water submarines, as against landmines, which are mostly stationary.

Generally there are many methods employed for the detection and diffusion of mines. Most of them rely of the characteristic traits exhibited by the mines themselves for their identification. Some of the more commonly used methods are: sensors, dogs, radars and other high tech methods [18, 20, 21, 22]. However in situations where technology could be costly brute force methods, which normally involve humans, are employed. Such methods are employed mostly in third world countries, which include many countries in

Africa, Central America, parts of Asia and Europe. In these methods huge ploughs, flails or rollers generally operated by humans are used. Normally, ploughs are used to clear roads or barren land by running across the whole area [21]. This is a very insecure method because there are a lot of un-defused mines left over after the process. These mines become potentially more dangerous since they are left just in the topsoil level. The chances of them exploding due to very small disturbances becomes very high. Flails are mechanical devices, which beat the ground by rotating drums, and the mines are exploded due to the impact. This also has a high percentage of potential leftovers. These methods are normally employed due to their economic feasibility in terms of cost and time.

Another very dangerous and brute way of defusing the mines is hand prodding [3, 4]. In this method humans are directly involved in the process of both detection and removal. A prodder is a device, which is in the shape of a knife and is used to prod the ground at an angle of around 35 degrees. The person should visually identify the mine for the detection. This method requires extreme skills. In countries where cheap labor is available, this method is called for. Sometimes magnets may be used for the detection process. This method may result in human loss and the de-mine rate is generally very slow and unreliable [20].

Normally in many instances sniffer dogs are used for the process of mine detection [20]. It should be noted that using sniffer dogs for the process could only help in detection and

not in removal. Dogs have extremely well developed senses and can be trained to detect explosives in trace quantities. This technique, however, requires extensive training of the dogs and their handlers (normally humans), and the dog's limited attention span makes it difficult to maintain continuous operations. Electronic chemical sniffers imitating the dog's natural senses are also used [20]. However, minefields are often saturated with vapors from detonated explosives, which limit the use of sniffer techniques for mine detection. Research is also in progress to construct dog-like robots, which can effectively substitute the dog's role in the process.

There are other advanced techniques that are fast emerging. Present technologies include ground-penetrating radar (GPR), global positioning systems (GPS), infrared thermography, thermal-neutron-analysis (TNA) [20, 22]. The TNA technique assumes that the explosives have a large amount of nitrogen compounds, which can be radioactive.

3.4 Sensor Technologies

- Ground Penetrating Radar: - GPR consists of a sensor that emits electromagnetic waves through an antenna and collects the reflected signals. Most often the antenna is wide band. The commonly used frequencies lie between 50 MHz and 100 GHz. This band is sufficient for capturing all the related information. GPR works on the principle that a rough surface would be more random in reflecting

the incident waves than a smooth surface. So the power of the received signal may vary with respect to the roughness or smoothness of the reflecting surface. Also the electrical properties of reflecting surfaces such as dielectric constant and permeability of the surface, which are functions of the material of the surfaces, can affect the absorption and reflection coefficient of the incident waves which may be useful in judging the presence or absence of mines. Soil humidity and wavelength of the electromagnetic wave can also be factors affecting reflection. Water content in the soil severely attenuates the incident waves. Experimental results show that low frequency waves can withstand attenuation when there are dielectric constant changes in the soil. GPR systems can be used for predicting the presence of mines within a particular resolution. Since the analysis involves a lot of parameters the prediction is normally poor unless we have a good knowledge of the processing parameters. Clutters (misleading results) due to man made objects, metals, etc, can make the false alarm rate more [22].

- Infrared sensors: IR radiation is the portion of the EM spectrum lying between microwaves and the visible region with wavelengths between 0.75 micrometers and 1 millimeter. Although all EM radiation produces heat, IR radiation can be more readily detected in the form of heat. When a material is heated it has the property of emitting infrared radiations. For this reason, IR radiation is also referred to as thermal radiation. The main advantage of using infrared rays for the

detection process is that they do not consume complex processing as in the GPR technique. Moreover visual pictures can be more comfortable for making decisions. However the accuracy of the detection process can highly depend on the environment and measurements. Two basic forms go into this category, photonic detection and thermal detection. In photonic detection energy particles or photons, which are released by materials, are measured and used in detection, whereas in thermal detection the rate of energy absorption measure is used for evaluation. Thermal detectors respond to only the intensity of absorbed radiant generally power regardless of the spectral content. Thus, they respond equally well to radiant energy of all wavelengths. The basic principle used in infrared thermography is that different materials surrounding the mine exhibit different thermal properties. This branch of study is called dynamic thermography [22].

- Ultrasound sensors: Ultrasound waves are basically waves of frequency greater than 20000 Hz. This technique is similar to the GPR technique. However the major point of distinction lies in the fact the ultrasounds produce vibrations of molecules in the medium through which they penetrate but radars do not. The fact that the speed of sound depends on the material through which it travels is utilized in the mine detection process. Sharp changes in media tend to impose themselves in sharp velocity changes, which can be captured. Ultra sound techniques are found to work in water medium better compared to air, quite contrary to the GPS technique [22].

The problems posed by sensors in the mine detection process are getting narrower due to advances in technology [20, 22]. When sensors with a great degree of accuracy is available, both in true detection of mines and minimizing false alarms, the trend of employing robots in the process looks feasible. Some of the main aspects to be looked at when robots deployed for the detection process are their ability to distinguish between mines and non-mines (reduce time wastage due to false alarms), their ability to operate under varied types of terrain and climatic conditions, their ability to detect a variety of mines, and their cost effectiveness in construction. Most of the times robots are employed in mine fields where the location of the mines is unknown. In such a scenario, a proper time effective foraging strategy has to be devised for the robot/robots. A multitude of heuristic and random strategies are employed for this purpose. Most of these strategies depend on the minefield and the construction of the robots themselves. These strategies should be designed to include the following issues: low cost and simple operation for the robots, durability of the robots, and quicker detection of the mines in terms of time. Some examples of mobile robots used in mine detection are lightweight robots like Pemex-BE, legged robots COMET-II, Vehicle Mounted Mine Detectors (VMMD), and suspended robots [20].

Before employing any robot for the demining process, the terrain should be prepared artificially to the needs of the mechanical aspects of the robots. Sometimes this may require removing of vegetation and other obstacles in the field, either by mechanical flails

or human hands. When robots are used for mine detection two questions arise. How are the robots detecting the mine and how are the robots removing the detected mines? Robots can be built with separate detection and removal strategies. Many of the robots are programmed to explode the mine when it detects it, but this could be dangerous in the sense that it can lead to physical damage to the robots employed. In other strategies mechanisms can be devised to carry the detected mine to a monitoring place where it can be safely exploded, but this would demand special abilities for the robots for the removal process.

Research in many parts of the world has focused on the utilization of heuristic techniques for robots in the mine detection process. Researches have experimentally found that using a number of robots could be more effective in the detection process as against a single robot in terms of cost effectiveness, time consumed etc [22]. Intelligence can be bestowed in the robots as centralized or distributed. In centralized intelligence, a robot could be partially or totally dependent on a central agency for advices and feedbacks. This is a type of master-slave relationship between the controlling agency and the robot entity. The central monitor could be humans, GPS (Global positioning systems) etc, which can communicate directly to the robot in sharing information. Traditional centralized control techniques are usually computational intensive and lacks robustness and flexibility [22]. A good solution for this could be by means of distributed control techniques. A distributed control environment does not have any centralized control, which monitors the individual robots. All of the robots are independent in decision-

making and execution, constraint by certain control laws. It is basically in this regard that Multi-Agent studies or Distributed Artificial Intelligence (DAI) come into the mine detection domain [1, 22].

The most inspiring form of distributed intelligence is biological intelligence. Nature bestows intelligence in various forms. Collective robotics is a division of multi agent theories that has been explored vastly in this regard. In collective robotics the individual robots (which are equivalent to a swarm in Nature) do not need to high coordination and communication complexity for executing their common goal. All of the robots manifest information on the environment and react suitably to the environment. The main problem that robots could face in a real minefield is that they can get disoriented or lost on their path, but since swarms do not share anything in common (no direct communication or reference) the system as a whole would not be affected much. In fact, these fluctuations from normal behavior can be used for more explorations, which could expedite the results. A good example for collective robots is the Growbots of the Idaho National Engineering and environmental Laboratory [20]. A good way of adaptive learning can be inculcated in the robots both about the environment (terrain etc.) and foraging knowledge. Algorithms should be robust enough to accommodate for false alarms, robot damages (which can result in the loss of robots in service), and misses in finding mines.

Modals employing genetic algorithms, cellular automata are also seen in literature for the devising of foraging strategies on mine detecting robots [22]. All of these models exploit

some mean of information interchange, which can grow adaptively with time. The main aim for most of the algorithms is to devise an effective probabilistic or deterministic strategy that complies with specification posed by the Humanitarian Demining Development Programme, quicker and with least hardware complexity for the robots themselves. In the next section we analyze how swarm intelligence based algorithms can be devised to study and solve the problem both at the simulation level and on a practical basis.

3.5 The Swarm Intelligence-based Solution

The agents are considered to be individual ants performing the task of pray detection and retrieval. In the process of detection the ants (special types of scouts) move from the nest and perform a random foraging of a given area. The foragers move in the random combined stochastic fashion while detecting the mines over the field. We tried to model the problem in accordance to that of a collective transport problem found in ant colonies. We assume that the mines are tantamount to the prey that the ants, which are all identical in behavior and movement, have to detect over an area. We give the ants a foraging strategy in order to scout for the mines. When an ant reaches a mine it spreads a scent around the mine in resemblance to SRR found in certain ant colonies. This scent decreases exponentially in a region around it. The spread of the scent is equivalent to physical stigmergy, which are basically physical changes produced in the environment so as to bring about a desired reaction, in this case attraction of other ants to the mine. The ants around the mine follow the scent's increasing gradient and finally land themselves at

the mine. We should note that the ants would not lose their foraging behavior even when they are intimidated by the scent about the presence of a mine in the locality. The basic point is that the following of scent is deterministic and no random movements are found inside the area covered with the scent. Thus the mine would be eventually defused when the required number of ants arrives at the mine's location. The problem is modeled in such a way that the attraction of the required number of ants is prefixed and not at the location of the mines. So the aspects of deciding on the number of agents to defuse a particular mine and transportation of it, are not important.

Some of the vital aspects involved in the problem are the guarrenty that a mine is completely defused and that of the time that the ants take in defusing all of the mines over a given field size. We assume that the field size over which the mines are distributed and number of mines that has to be defused is known. This eliminates the problem of assuring that all of the mines are detected, though the time taken for defusing all of the mines may need to be minimized in certain instances. This may require a good foraging strategy; though increasing the scent spread area can minimize the time taken for defusing all the mines. We have given a probabilistic combined deterministic strategy for this case. The strategy that can be employed and the assumptions needed for it are detailed in this section. The mine detection problem involves the detection and the demining of randomly placed mines over a field by a finite number of agents with resource constraints such as lifetime of the agents [10, 11, 12]. The mines were uniformly distributed over a field in our simulations. The demining of any mine involves

the collective actions of a certain number of ants, four in our simulations. The main goal of the work is to eliminate the central intelligence in the completion of the task. This need for a collective action of a certain number of ants for demining brings the recruitment mechanisms into the picture.

When an ant reaches a mine it spreads a scent around the mine in resemblance to short range recruitment (SRR) found in certain ant colonies [1, 2, 4, 6]. The scent decreases exponentially in a region around it as shown in Figure 1. The formulation for the scent decay in our simulations is shown in equation 1. The spread of the scent is equivalent to physical stigmergy, which are basically physical changes produced in the environment so as to bring about a desired reaction, in this case attraction of other ants around the mine to the mine. The ants around the mine follow the scent's increasing gradient and finally land themselves around the mine.

Let S be the scent intensity at any point (x, y) on the minefield, the point (x_1, y_1) is the location of the mine, with A and α being constants in equation 1. In our simulations A is 1 and α is 0.3.

$$S(x, y) = Ae^{(-\alpha(\text{Min}((x-x_1), (y-y_1))))} \quad (1)$$

The approach that we have used for the mine detection problem is a combination of both deterministic and stochastic methods. We bring in the stochastic component only in the foraging stage, while the stage when an ant enters a scent area it does not behave

stochastically, but rather in a deterministic manner. It simply follows the route, which has an increase in the scent, and since the intensity of the scent peaks at the mines, the ant eventually finds itself at the mine. The behavior of the ants can be put in a state machine representation. The state machine has three distinct states:

- Behavior 1-Foraging
- Behavior 2-Scent Following
- Behavior 3-Waiting

From the state machine it can be seen that ants can proceed from one state to the other state for any combination of two states under some conditions, except for that of behavior1 to behavior 2. We shall elucidate the conditions for all of the states. Tables 1 and 2 illustrate the conditions of the state changes and the expected reactions of the mine detection algorithm respectively.

Table 1. State Changes in the Mine Detection Algorithm

No.	State Change	Conditions
1.	Behavior 1 to Behavior 2	When a foraging ant detects the scent
2.	Behavior 2 to Behavior 3	When an ant follows the scent concentration to a mine or a mine in its trajectory of scent follow
3.	Behavior 2 to Behavior 1	When the maximum of the scent intensity around becomes zero
4.	Behavior 1 to Behavior 3	When a foraging ant detects a mine
5.	Behavior 3 to Behavior 1	When an ant has waited at the mine for a specific time When the mine at which it has been waiting is defused
6.	Behavior 3 to Behavior 2	When an ant has waited at the mine for a specific time, but finds a scent around the same or different mine. When the mine at which it has been waiting is defused but finds a scent immediately for another mine.

Table 2. Expected reaction for state changes in the Mine Detection Algorithm

No.	State Change	Reactions
1.	Behavior 1 to Behavior 2	Initiate the scent sensor (in addition to the mine sensor, which should be read first), which can read, scent intensities at all of the points around it and picks the point with maximum intensity to go to. If mine found go the behavior 3.
2.	Behavior 2 to Behavior 3	Do not activate scent spreading tag
3.	Behavior 1 to Behavior 3	Activate the scent spreading tag, which spreads the scent.
4.	Behavior 3 to Behavior 1	Deactivate the scent spreading tag if it is activated
5.	Behavior 3 to Behavior 2	Read scent sensor

An important concept that is observed when all of the ants go into the state of waiting for the others to come to their respective mines is called *freezing*. Such a situation can happen when the ratio of the number of ants involved in the detection process to the number of mines deployed is relatively small. There are a number of other factors that can dictate the occurrence of such a phenomenon. Some of them are the field size and the initial distribution of the mines. Such a situation is called *freezing*, where there is no motion of the ants and all of the ants are waiting infinitely for the others [7, 8].

In the mine detection problem, the phenomenon of freezing could be avoided by enabling the ants to have a threshold time to wait at the mine. If the required number of ants (in our case, four) does not arrive within the stipulated time (the threshold waiting time) the ant leaves the mine and resumes its foraging behavior. For the simulation to have an even platform, we program the ants to have a *scent-spreading ability*, which when activated the ant has the ability to spread the scent. The scent-spreading tag of any ant gets activated when an ant finds a mine without the help of the scent of any other ant irrespective of other ants waiting at the particular mine. Only the ant that has the scent spreading activated has the ability to quench the scent when it decides to stop waiting and resume foraging. Thus every mine (if detected) has the same scent distribution in magnitude and direction around it. This is seen in the state diagram representation of the mine detection problem. Another interesting problem to be looked upon is the amount of time that any ant should be allowed to wait at a particular mine. This can be a function of the probability of any ant being found at a particular spot on the field per unit time, the

number of ant, and the number of mines. By employing this strategy the whole mine detection problem can be explained as in Figure 2.



Figure 2: The Mine Detection Algorithm

Ants have been found to have a threshold in attempting to retrieve a pray item from its location [1, 10]. If the ant finds the pray to be too heavy or very resistant to movement (traction), the behavior of the ant changes. In the one ant case, while pulling the pray, SRR is forsaken and LRR is resorted to. When there is a group of ants trying to pull the pray (the pray in-subordinating to motion), the amount of force exerted by the ant to influence the pray decays with time. It is shown that the amount of ants joining the group of pulling ants decreases with time when the motion of the group pulling the pray is slow [1, 16, 17].

When the mines are densely concentrated over the field, there may be instances where two or more scents can overlap. In such instances, the algorithm should ensure that the peaks in scent intensity occurs only at the mines and that there are no or very fewer local maxima in the overlap region, which may mislead the ants as the ants within the scent area, moves only toward the increase in scent concentration. Local maxima, which can normally occur in the overlap region, could be detrimental in restricting the movement of the ants within the scent spread region. The behavior that the ants' exhibit when they enter the scent spread regions is following the increasing gradient of the scent concentration. When local maxima occur within overlapped region ants could be trapped. The ants stop their motion until the local maxima disappears. Thus the ant is unavailable for the task for a short duration though this duration is short lived. It should be noted that this will not lead to a false detection of mines as the behavior of ants in the scent spread region is two-fold: scent following and sensing for mines themselves. At the

local maxima since there are no mines the ant would not go into waiting mode (behavior 3). Therefore this problem is not drastically detrimental it needs to be considered in the overall interest of the problem. We have devised a method to minimize the ants falling in the overlap region. The method assumes that if we avoid ants which are normally outside the overlap region from entering the overlap regions of scent the problem could be avoided. The basis for such a consideration is given below.

For the spread of the scent we use a falling two-dimensional exponential decaying function. This may be good enough when there is no overlap in the scent regions, but the exponent for the scent distribution needs to be adjusted when there are overlaps of scent fields. Let us explore a scene where two overlaps have occurred and how the exponent should be modified. Overlap of scent regions (Figure 3) on the simulation (rectangular overlaps of three scent regions) takes place in the following manner. The mines are located at the center of the rectangle. The scent concentration peaks at the center of the rectangle and exponentially falls to the boundaries.

Let the exponential fall go according to the function $f(x) = a^x$ for x values ranging from 0 (at the center of the mine) to m (the value it takes at the boundaries). Therefore if a lies in the range 0 to 1, m is the largest value that x can take. If we were to prevent an ant entering an overlap region from outside (for e.g. preventing from entering the shaded region in Figure 3 from anywhere in the non shaded region), the scent concentration

along the boundaries (e.g. point X in Figure. 3) should not be greater than that of the value just outside it (point Y in Figure. 3)

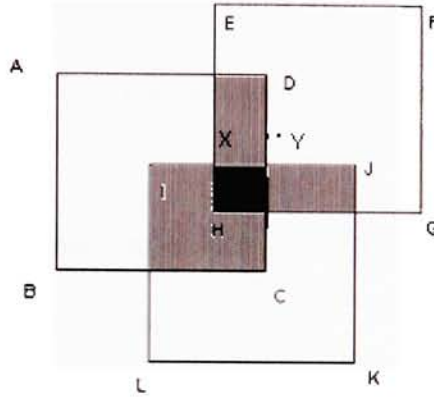


Figure 3. The overlap of three scent spread regions

Therefore,

$$a^{n+1} + a^m \leq a^n \quad (2)$$

where a^n is the scent contribution of the at point Y (point immediately outside the boundary) and a^m is the scent contribution at point X (point along the boundary). Scent contribution by independent rectangles are additive.

From (2)

$$a^n (1 - a) \geq a^m \quad (3)$$

Taking the logarithm of both quantities of the inequality,

$$n \log(a) + \log(1 - a) \geq m \log(a) \quad (4)$$

$$(m - n) \log(a) \leq \log(1 - a) \quad (5)$$

The worse case (the case when the quantity $(m - n) \log(a)$ is closest to the constant $\log(1 - a)$), can occur when n takes the value $m - 1$

So we substitute $n = m - 1$ in inequality (5)

$$\log(a) \leq \log(1 - a) \quad (6)$$

Therefore

$$a \leq 1 - a \quad (7)$$

This occurs only when a is in the range 0 to 0.5

Thus we see that the overlaps poses a constraint on the exponent we can pick for the construction of the exponential fall.

Thus we see that for condition (Equation 2) to be valid, a (the exponent of the scent distribution) should be a number, which is in the range 0 and 0.5. We see that for two overlaps the range of values that the exponent can take becomes narrower. This trend is seen to happen, as there are chances of more than two overlaps happening. Thus the concentration of the mines poses a constraint in the value that the exponent of the distribution can take. The problem of analyzing the regions with more than one overlap grows exponentially with the number of overlaps. A common trend though is that the range of values that a can take becomes narrower as the number of overlaps increases, if we were to avoid the occurrence of a local maxima in the overlap region largely. A feature to be observed is that the area of the scent spread has no effect on the exponent of the distribution, though it can affect the number of local maxima occurring in the overlap region.

In the mine detection context a basic foraging strategy (minimize the time taken by the agents to detect all of the mines) has to be devised. Here we assume that the number of mines is a small percent of the field size. This assumption emphasizes the fact that a large amount of time spent by the agents is on foraging (checking for the presence of a mine). Therefore if we were to devise a basic foraging strategy we conserve a lot of time on the whole process.

During their foraging period the agents always move towards a randomly generated point on the field. Basically, the ants can have an apparent mapping of the field into a certain

number of regions, which can equivalent to the cognitive maps or the visual cue information that the ants are capable of having. An ant can randomly generate a point in a randomly generated region and move towards the point in a deterministic manner or perform a random walk towards the point. For our analysis we have considered the deterministic nature of ant movement. The deterministic movement towards the point is two fold, first along one axis then along its perpendicular axis. During this motion if they come across a mine or enter into a field of scent they change their behavior. An ant's motion along one direction is independent of its perpendicular direction. Let us consider the one-dimensional case and extend it the two-dimensional case utilizing the fact of independency.

Let us begin the analysis with the calculation of the probability of any point on a one-dimensional line. Initially the agent is at one end of the line. It randomly generates a point on the other half of the midpoint of the line and starts moving towards the point. After reaching the point it randomly generates a point on the first half and moves towards it. This process, which is similar to a random walk, is repeated continuously. In this situation the probability of a point being visited by the ant is given as follows.

Since the random point generation is symmetric about the midpoint, we can consider each of the halves separately for the analysis. Let us consider each half to be of length a and

x the distance of the randomly generated point from the midpoint of the line. The probability that an agent per unit time visits a point is as follows

$$P = 0.5 \int_x^a \frac{1}{x} f(x) dx \quad (8)$$

where $f(x)$ is the distribution by which the points are generated.

Extending to the two dimensional case we get

$$P(x, y) = \left(0.5 \int_x^a \frac{1}{x} f(x) dx \right) \left(0.5 \int_y^a \frac{1}{y} g(y) dy \right) \quad (9)$$

Let us assume that the points are generated uniformly on either side of the midpoint.

Therefore $f(x) = \frac{1}{a}$ for $0 < x < a$

This gives that

$$P = 0.5 \int_x^a \frac{1}{x} \frac{1}{a} dx = 0.5 (\log(a) - \log(x)) \quad 0 < x < a \quad (10)$$

A quick check reveals that $2 \int_0^a P dx = 1$ (11)

For the two-dimensional case

$$P(x, y) = 0.25(\log(a) - \log(x))(\log(a) - \log(y)) \quad (12)$$

An assumption that we make here is that the best foraging strategy could be devised if we find a function $f(x, y)$ for which the distribution P is the same as the distribution of the mines over the field. Finding P demands the Equation 12 to be solved.

Let $h(x, y)$ be the density with which the mines are distributed over the field. The expression then to be solved is

$$P(x, y) = \left(0.5 \int_x^a \frac{1}{x} f(x) dx \right) \left(0.5 \int_y^a \frac{1}{y} g(y) dy \right) = h(x, y) \quad (13)$$

Using the fact x and y are independent the above expression in the two dimensional case could be reduced to the one-dimensional case. Therefore the expression reduces to

$$0.5 \int_x^a \frac{1}{x} f(x) dx = h'(x) \quad (14)$$

where $h'(x)$ is the marginal density of $h(x, y)$

Differentiating the above expression on both sides with respect to x

$$\frac{d}{dx} \left(0.5 \int_x^a \frac{1}{x} f(x) dx \right) = \frac{d}{dx} h'(x) \quad (15)$$

$$\text{Let } \int_x^a \frac{1}{x} f(x) dx = F(x) \quad (16)$$

$$\frac{d}{dx}(0.5(F(a) - F(x))) = \frac{d}{dx}(h'(x)) \quad (17)$$

$$-0.5 \frac{d}{dx}(F(x)) = \frac{d}{dx}(h'(x)) \quad (18)$$

$$f(x) = -2x \left(\frac{d}{dx} h'(x) \right) \quad (19)$$

The above expression represents how $f(x)$ should behave in the one-dimensional case. Since we assume that the movement of the ants is independent along the two dimensions of the field, an extension of the above result for the two-dimensional case can be easily carried out. The main point to be noted is that for $f(x)$ to be a probability distribution function the differential of the marginal density function $F(x)$ of the mine distribution should have negative slope on either side of the midpoint in the one-dimensional case. Further care should be taken that $f(x)$ integrates to 1 to be a valid probability distribution.

When the distribution of the mines is not known forehand the assumption of it being uniform can be made. Unfortunately a closed form solution for $f(x)$ does not exist for the uniform distribution case. This is true for many other distributions too. But in all of the cases a discrete approximation can be made for $f(x)$ to suit the particular distribution since the field is normally discrete.

4. Analysis and Results

Simulations were run over field sizes of 100x100. The distribution of the mines was done uniformly and the foraging strategies given to the mines were the deterministic walk (Figure 5) and the random walk (Figure 6). We acknowledged that the time required for the ants to completely clear the field (defuse all of the mines in the field) as the good criterion for reporting the efficiency of the mine detection process. The results obtained are tabulated in this section. Results obtained are ensembles of averages of five independent runs conducted with same approximation platforms. Figure 4 shows a sample simulation of the mine detection problem on a 100x100 minefield.

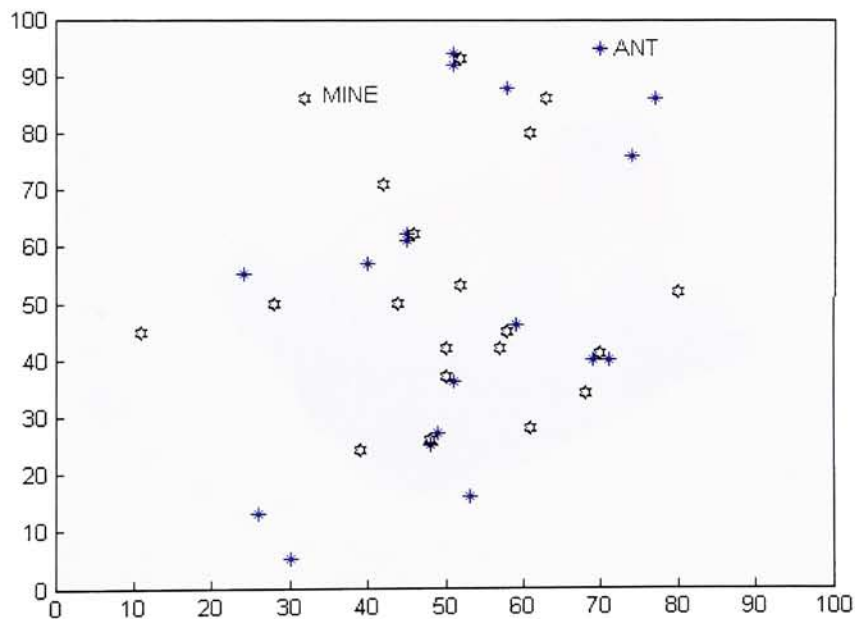


Figure 4. A Sample Simulation- The Mine Detection Problem

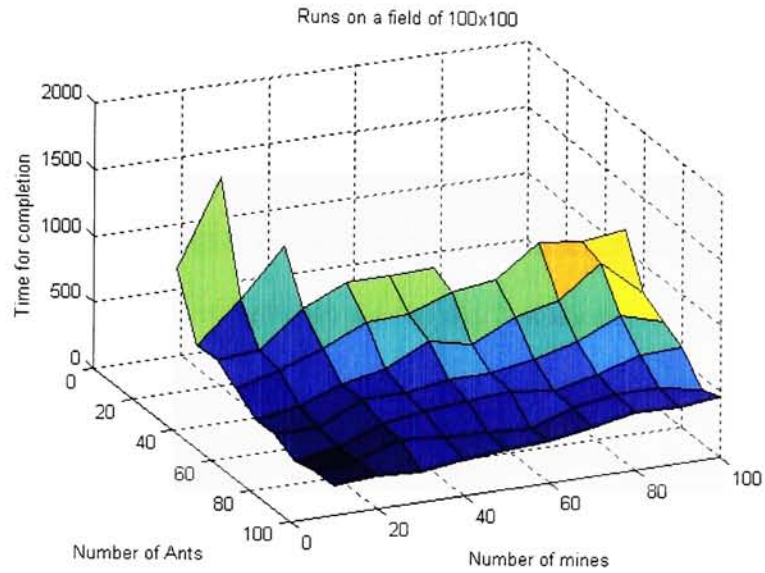


Figure 5. Results for runs on a 100x100 field with deterministic motion

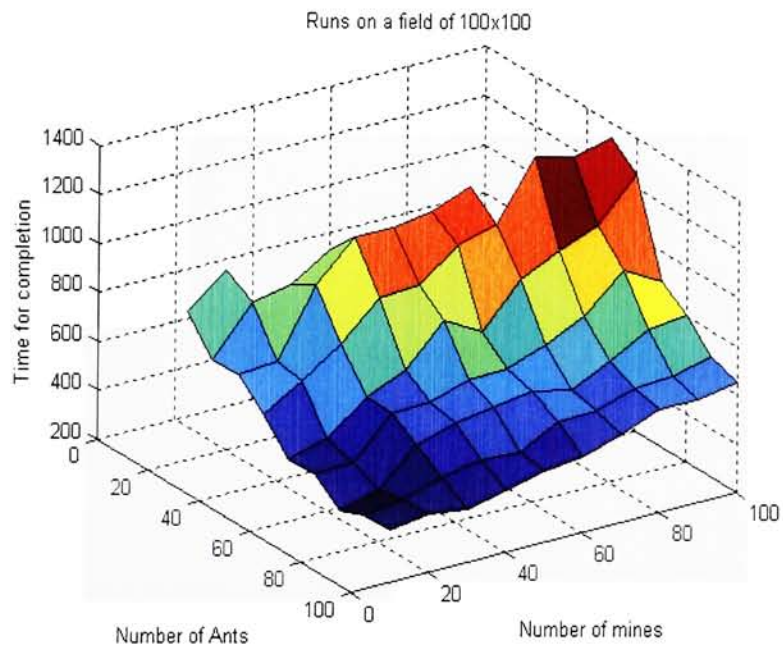


Figure 6. Results for runs on a 100x100 field with random walk

Freezing, though considered negative is an observable feature. Its dependence on the various parameters of the problem is shown on Figure 7. The curve shows a sixty percent failure line, when the mines were distributed uniformly over the field. Points on the line define the ant-mine combination for which the simulation results showed freezing sixty percent of the time. From the simulation we can see that the curve of freezing depends on the field size.

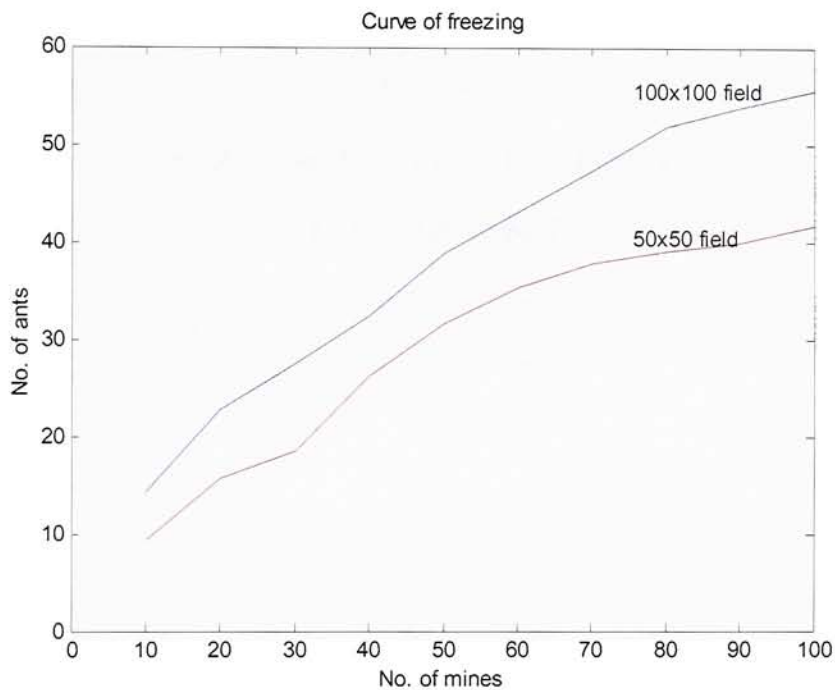


Figure. 7. Curve of freezing (sixty percent failure line)

Incorporation of cognitive maps and cognitive memory to the ants produced better results in comparison to random motion ants' presented above. The foraging strategy for the ants is basically given by in accordance with the cognitive maps. Cognitive maps are

distinctive regions called *cognitive regions* on the minefield, which may or may not be mutually exclusive. Figure 8 shows a field divided into distinctive cognitive regions. The regions A , B , C , and D shown in Figure 8 form the four cognitive regions. Each cognitive region can be divided into sub regions called *cognitive sub-regions*. The ants are given the capacity of *cognitive memory*. The cognitive memory in the ants is the ability to retain information of mine locations. Utilization of the information of the mine locations in devising foraging routes results in lesser time for the completion of the mine detection task. Navigation of the ants over the field, in the case of foraging is basically roaming the cognitive regions. The processing of the information present in the cognitive maps controls the sub regions that they visit during navigation. In the case of mine detection the processing should be aimed at optimizing the route so as to visit routes where the likelihood of finding mines is larger.

Let, $a_{1d}, a_{2d}, \dots, a_{nd}$ and $a_{1u}, a_{2u}, \dots, a_{nu}$ be the knowledge of the defused and un-defused mines in regions A_1, A_2, \dots, A_n in cognitive region A on the field shown in Figure 8. Similarly let $b_{1d}, b_{2d}, \dots, b_{nd}$ and $b_{1u}, b_{2u}, \dots, b_{nu}$ be the knowledge of the defused and un-defused mines in regions B_1, B_2, \dots, B_n respectively. The number of distinctive sub region in a cognitive region is n . An ant would tend to select a new course according to the following probability distribution. An ant moving from point X to point Y in the field is shown in Figure 8. Let us assume the coordinates of points X and Y with respect to a certain boundary (in our simulations the origin was at the lower

left corner) is (x_1, x_2) and (y_1, y_2) respectively. The probability distribution function of the ant choosing its destination cognitive sub region among various cognitive sub regions is modeled as given in the Equations 20 and 21.

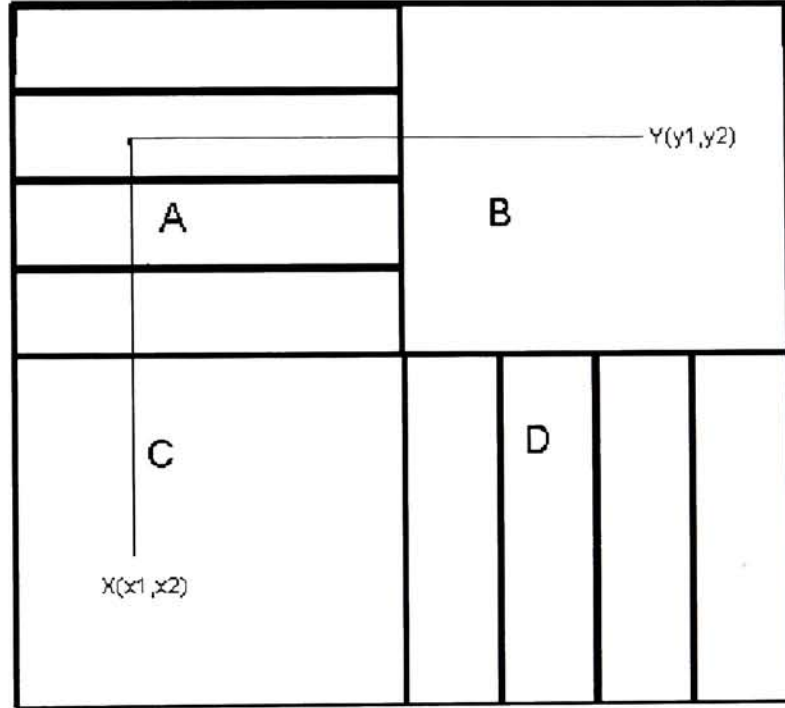


Figure 8. Minefield plotted into cognitive regions

$$P(y_1 \in B_k) = \frac{1}{(1+\beta)} \left(\frac{N-b_{kd}}{(n-1)N} + \beta \frac{b_{ku}}{M} \right) \quad (20)$$

$$P(y_2 \in A_k) = \frac{1}{(1+\beta)} \left(\frac{N-a_{kd}}{(n-1)N} + \beta \frac{a_{ku}}{M} \right) \quad (21)$$

β in the Equations 20 and 21 give the degree of relative importance given to the information gleaned during previous foraging raids. As we can see from Equations 20 and 21, as β is increased the relative importance of the information regarding the undefused mines overweighs itself against the defused mine information in the probabilistic functions given in Equations 20 and 21. β being unity gives egalitarian importance to both. The quantities M and N represent the total knowledge of the defused and undefused mines during foraging. They are represented as shown in Equations 22 and 23.

$$N = \sum_{k=1}^n a_{kd} \quad (22)$$

$$M = \sum_{k=1}^n a_{ku} \quad (23)$$

The comparative results can be analyzed using simulation results obtained through runs conducted on fields of 96x96 and 48x48 with varying number of ants and mines as they were multiples of numbers used for field sub sections and field maps. The results obtained are shown in Figures 9 and 10. The respective curve of freezing is shown in Figure 11. Another performance measure is the reduction factor. The reduction factor is defined as the ratio of the performance of the ants with and without cognitive memory. The relationship can be laid down as follows

$$T_r = \frac{T_f}{T_w} \quad (24)$$

T_f and T_w are the respective time iterations for complete a specific mine detection task by the ants without and with memory respectively. Figure 11 shows the performance of the ants against the reduction factor.

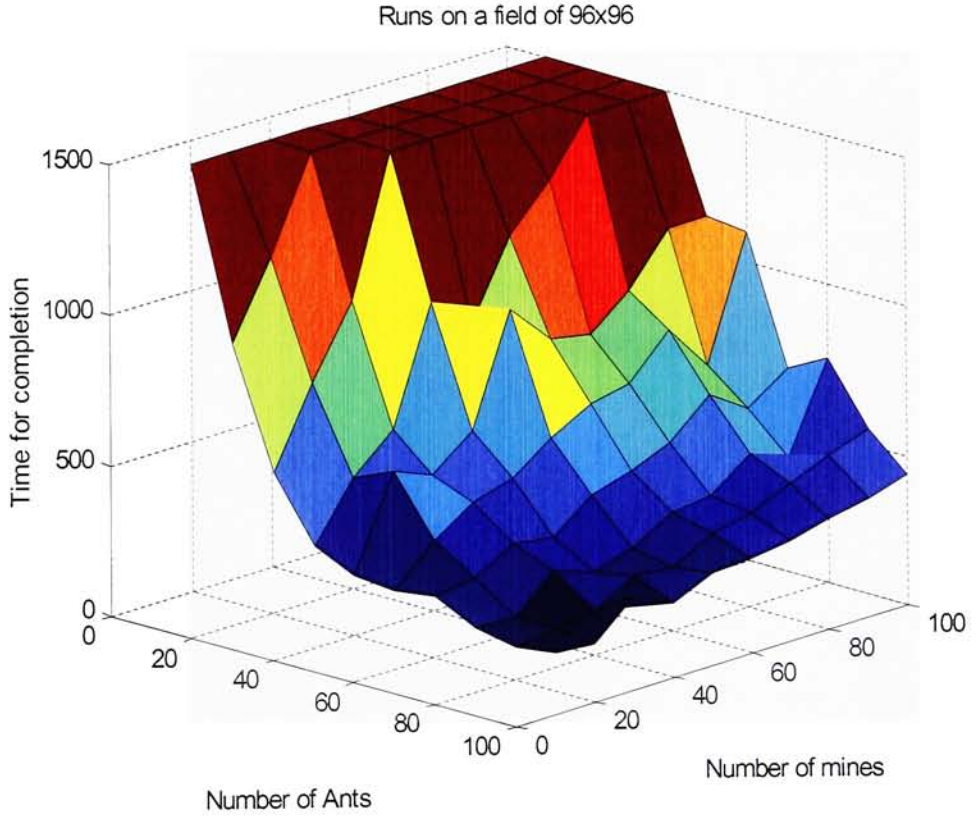


Figure 9. Runs on 96x96 field for ants equipped with cognitive memory

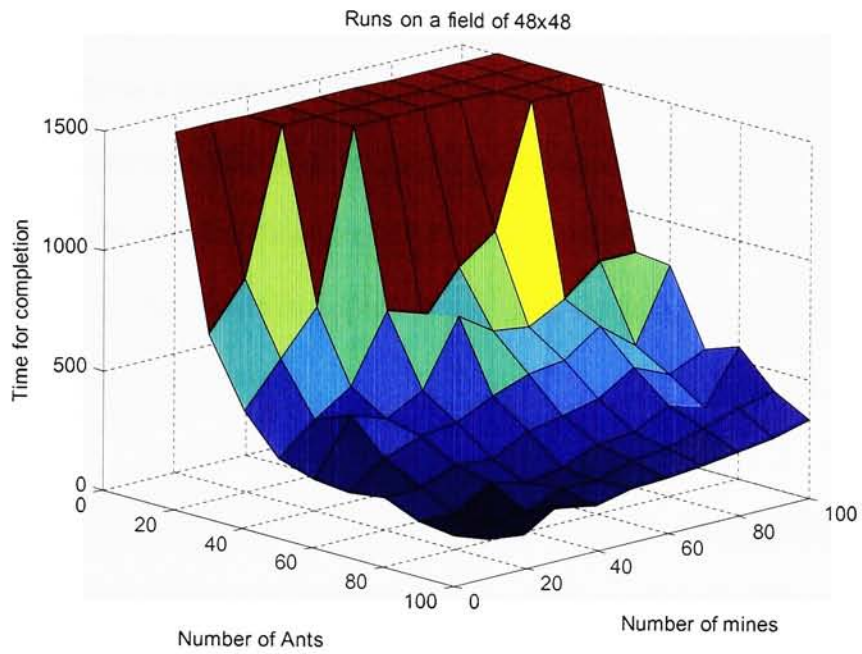


Figure 10. Runs on 48x48 field for ants equipped with cognitive memory

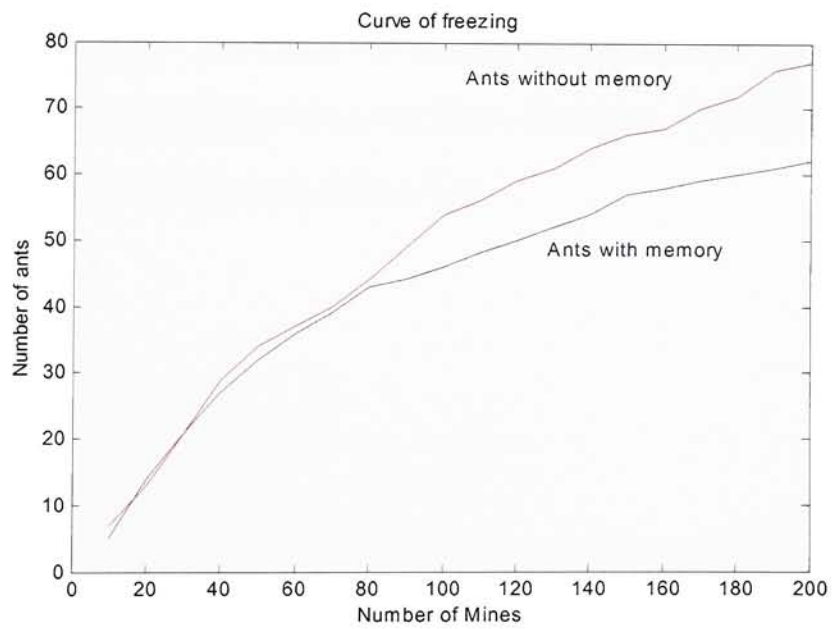


Figure 11. Curve of Freezing

Figure 12 shows the comparison of the reduction factor to the knowledge ratio β . We observe that there is a maximum value for the reduction factor seen in our simulation results. The maximum value signifies the highest point of adaptivity for the particular ant-mine ratio. On practical levels when prior information on the number of ants and mines are available, this observation proves very good in fixing the knowledge ratio β for obtaining maximum adaptivity.

From the above results the following analysis could be made. The reduction factor tends to increase when the mines to ants ratio is high, thus necessitating the employment of cognitive maps in the foraging ants under such situations. It is evident from Figure 13 that the rate at which the mines are defused progressively increases in the case of ants employed with cognitive maps whereas it decreases or is stagnant in the case of those without cognitive maps. The decrease in the rate of mine detection as time progresses reflects randomness and increase in the rate shows adaptation. Thus adaptivity is clearly seen in ants employed with memory (Figure 14).

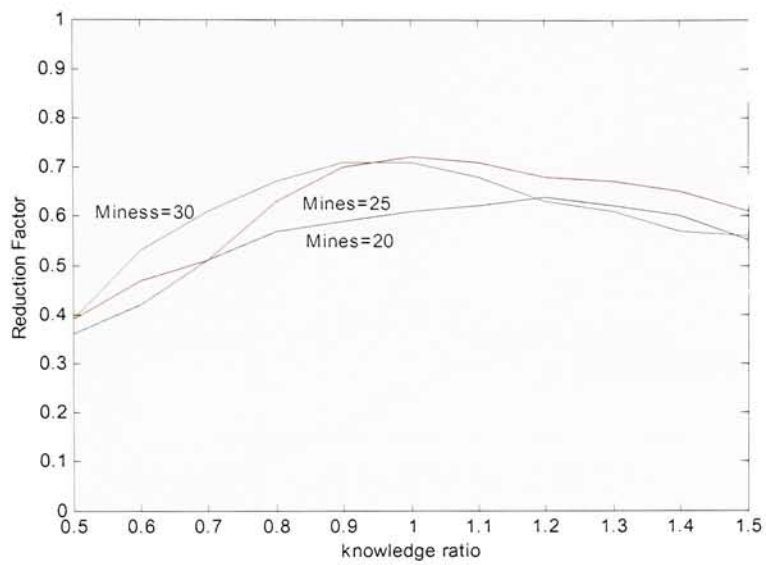


Figure 12. Performance curve against Reduction Factor

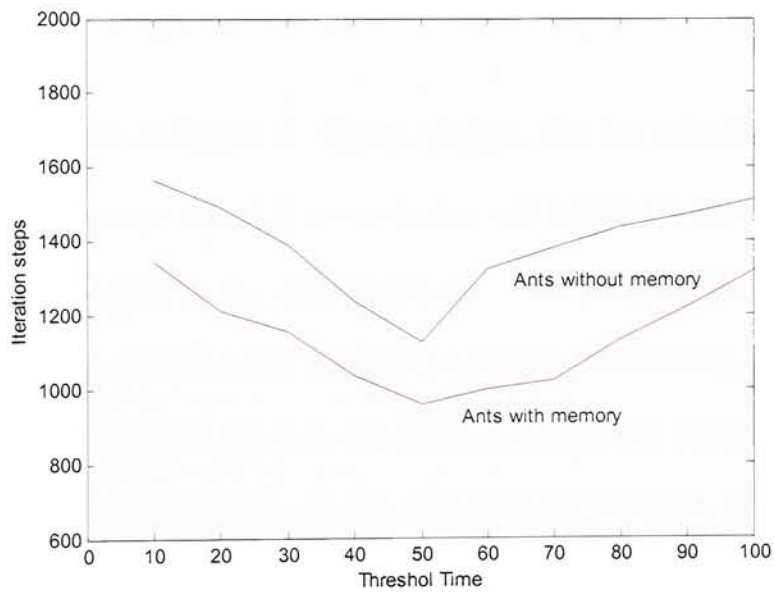


Figure 13. Comparative performance of ants with and without cognitive memory on a 96x96 field

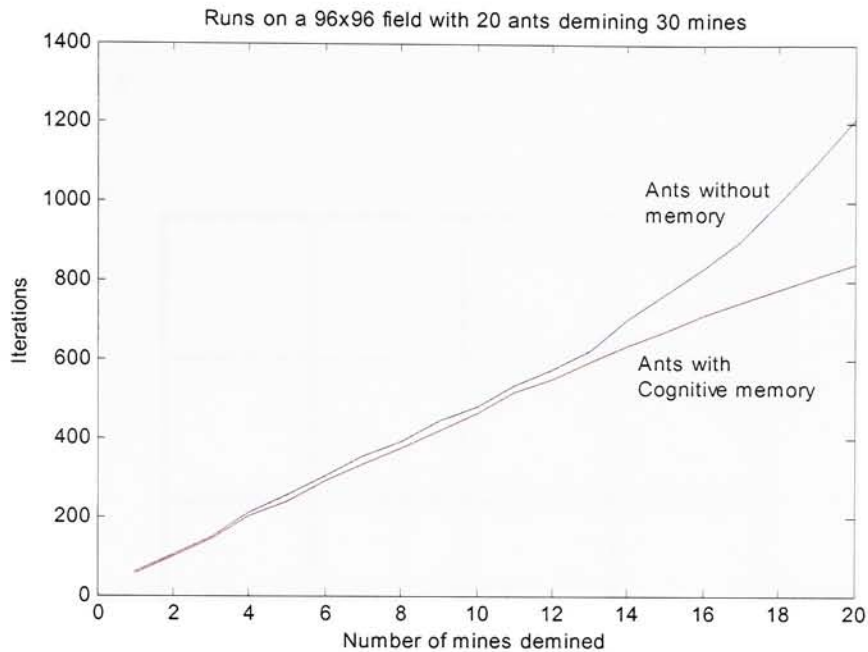


Figure 14. Progressive demining of ants with and without cognitive memory

The comparison plots in Figure 12, 13 and 14 show that the reduction factor is highly significant. An important aspect in ant navigation and foraging is the aspect of cognitive meandering incorporated in the forging process. The foraging strategy for the ants involved in the mine detection task is based on cognitive meandering over the field [13, 14, 15]. In this strategy the ants map the foraging terrain, into regions called cognitive regions. The ants are initially assumed to start from the boundary of the minefield for practical reasons. During foraging, the ants meander from one cognitive sub region to another. The ants have the ability to locate themselves at any point within the minefield with respect to certain references. The reference in our case is the boundary of the

minefield. Figure 15 shows an ant moving in the realm of the cognitive regions from point *A* to point *B*.

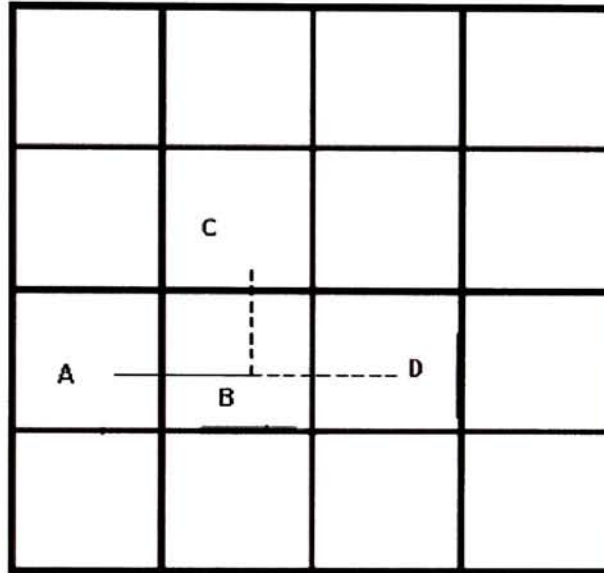


Figure 15. Cognitive map based ant foraging- Cognitive Meandering

At point *B* the ant has to decide on which cognitive region to choose from its neighboring cognitive regions. This decision is made based on the knowledge of the mines it has demined in its adjoining regions. The ant in cognitive region *B* may choose to go to cognitive region *C* or to cognitive region *D* based on the fact that either *C* or *D* has the highest probability of detecting mines in them. Another fact on which this decision can be made is the history of visits made to cognitive regions *C* or *D*. If two or more cognitive regions are equally weighed in terms of the ant's knowledge then a random decision is made.

In our simulations, we have modeled the local decision of the ants in picking the foraging cognitive region based on the demined/undemined mine knowledge of its adjoining cognitive regions. The probability distribution function used in the model is given is Equation 25. The term β in the equation is a measure to show the relative importance of the demined and undemined mine knowledge of the ants.

$$P(cognitive_region_k) = \frac{1}{(1 + \beta)} \left(\frac{N - b_k}{(n - 1)N} + \beta \frac{a_k}{M} \right) \quad (25)$$

In Equation 25, N and M represent the total knowledge of the mined and demined mines in the adjoining cognitive regions of the ant's present cognitive region. Terms a_k and b_k represent the undemined and demined information of $cognitive_region_k$ adjoining the ant's present cognitive region. The fact Equation 25 sums up to one over the entire ant's adjoining cognitive regions assure that it is a valid probability density function. The following results in Figures 16, 17, and 18 illustrate the performance of ants foraging using concepts in cognitive meandering.

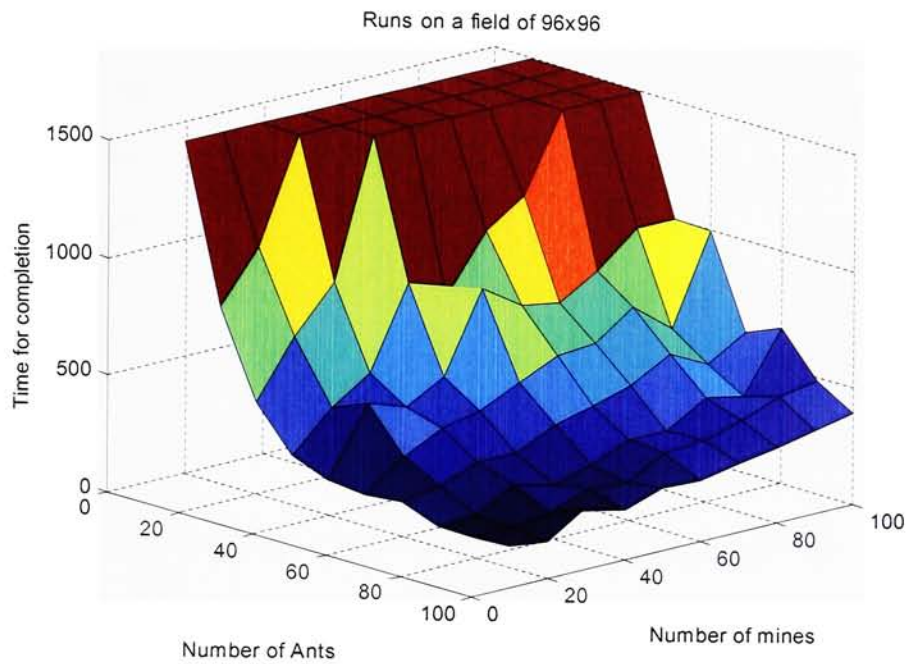


Figure 16. Runs conducted on a 96x96 field-Cognitive Meandering

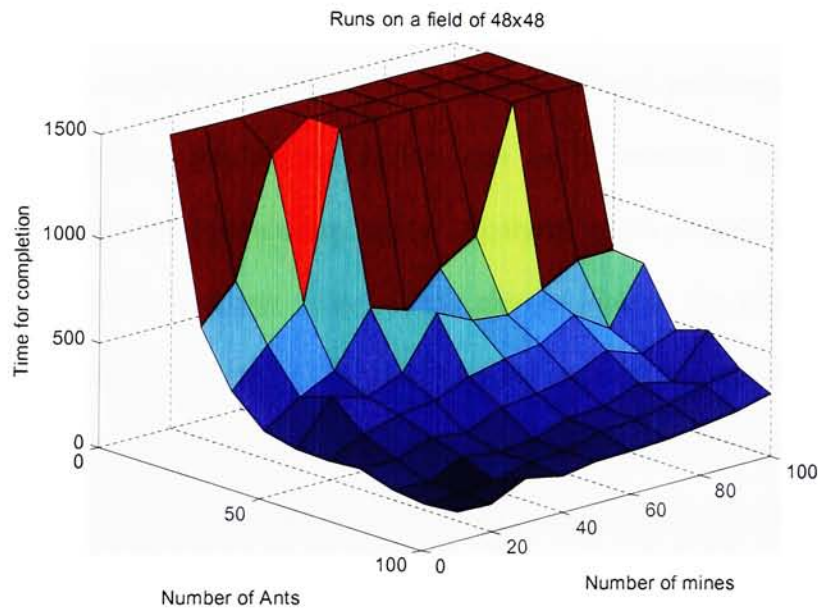


Figure 17. Runs conducted on a 48x48 field-Cognitive Meandering

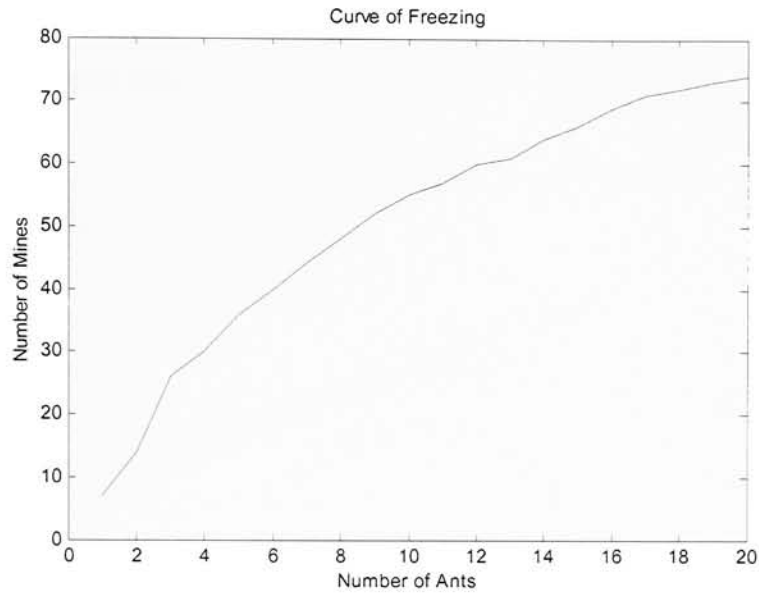


Figure 18. Curve of Freezing-Cognitive Meandering

Figure 19, 20 and 21 present the study conducted with simulations using cognitive meandering. The comparison of the curve of freezing of both performances of ants with and without cognitive meandering ability can be a measure for evaluating the performance of cognitive meandering ability. Analysis shows a feeble advantage for the cognitive maps in ant foraging. One should always look at the effectiveness of the cognitive maps built in the ants. The reduction factor is a good measure showing this effectiveness. The reduction factor varies with combinations of field size, number of ants deployed and number of mines present. A study showed in Figure 20 shows that the reduction factor has an optimal lowest value for a given combination of field size. This was a study conducted on a 96x96 field with thirty mines randomly distributed of it. This

becomes instrumental in picking up the optimal number of ants to be deployed for a specific mine detection task.

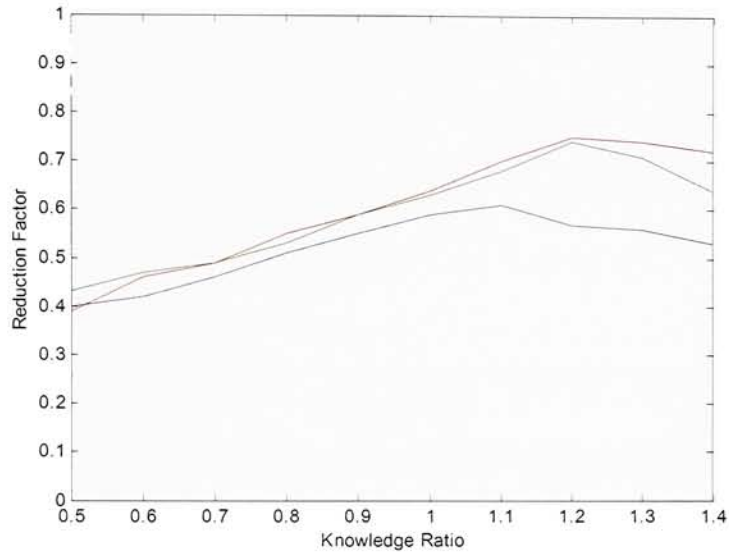


Figure 19. Performance curve against Reduction Factor-Cognitive Meandering

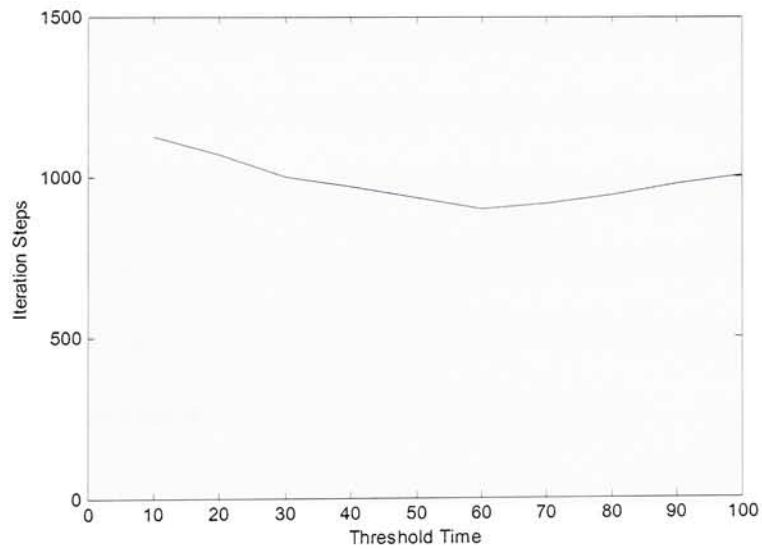


Figure 20. Comparative performance of ants with and without cognitive meandering ability on a 96x96 field

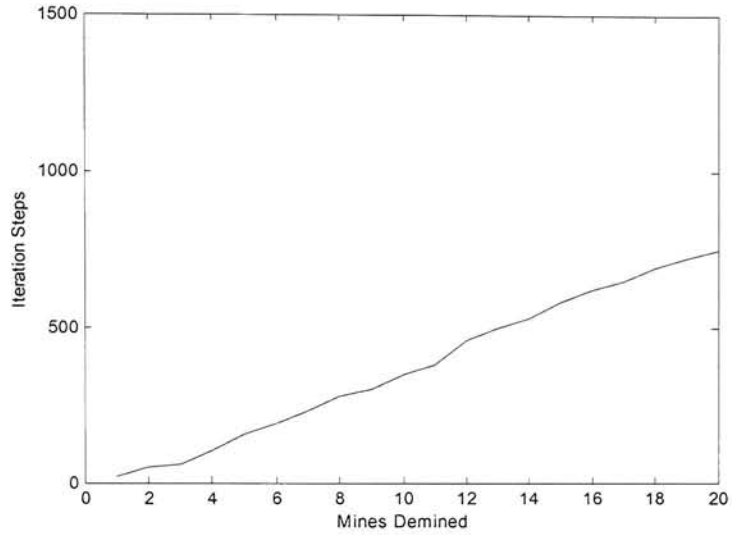


Figure 21. Progressive demining of ants with cognitive meandering ability

Variation in the value of β was found to affect the performance of the ants. Figure 19 illustrates the change in reduction factor against β , for runs on a field of 96x96 for various counts of mines. We see in our simulation results that the reduction factor was optimal for a specific value of β for different number of total mines. This follows the trend that the optimal reduction factor would be greater when the ant-mine ratio is greater as a result of more time for adaptivity. Generally it was seen that ants optimal reduction factor occurred for instances where the ant-mine ratio was more when the β value more than unity. This shows natural adaptivity of the whole system.

5. The Implementation of the Ant Algorithm with GroundScouts

Groundscouts robots were used to demonstrate multi agent capabilities of the algorithm at a more practical level. The architecture and design of the groundscout robots were carried out as a part of the ongoing research activities at the Multi Agent Biorobotics Lab, EE, RIT. I would personally like to thank Brett Youngstrom and Kevin Krigbaum for their cooperation and association in the design and development of the groundscouts. The groundscout robots have many hardware layers with unique capabilities. The hardware layers included a locomotion layer, a power layer, ultrasonic, proximity and infrared sensors, a control layer and intra robot communication layers. The robots were designed to be modular and are programmable to suit other application. Some of the applications for which the groundscouts can be programmed include surveillance and security, mine detection, reconnaissance, and search and rescue missions. The basic constructs of the groundscouts are shown in Figure 22. Each layer was responsible for a group individual function, which would be collectively organized and controlled by the control layer. The individual layers that form the architecture of the robots are given as follows.

- The Locomotion Base
- The H-Bridge, Proximity and Power layer
- The Ultrasonic layer
- The Infrared layer

- The Control layer
- The Communications layer

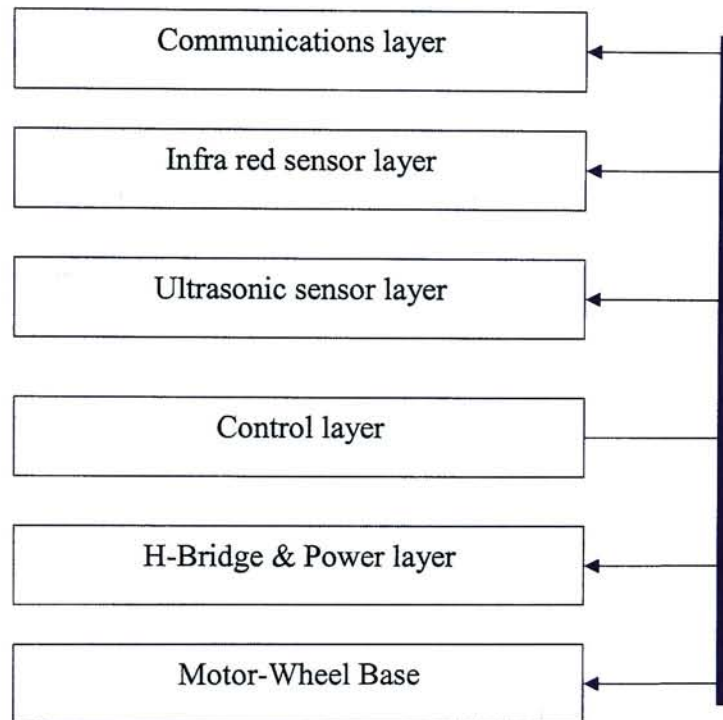


Figure 22. Component blocks of the Groundscouts

The locomotion base of the robots carries the motors and wheels required for locomotion and navigation. There are two motors controlling four wheels in the base by an axle-gear arrangement. The locomotion base also has a reserved space to carry the batteries to

power up the entire system. The batteries that were used for the power up circuitry were AAA NiMH rechargeable batteries. Each of the batteries was able to supply 1.2 V.

The immediate next layer on top of the locomotive base was the H-Bridge, proximity and power layer. The purpose of this layer was charging the batteries on the locomotive base, sensing motor ticks and providing directional information for the motors in the base. The H-Bridge circuitry housed in this layer provides the directional control for the motors in the locomotive base. This layer also has three proximity sensors, which can detect objects very close to the robot.

There are two sensory layers in the architecture of the robots. They are the ultrasonic sensors and infrared sensors. The ultrasonic sensors are capable of detecting obstacles at a range of 3 to 300 centimeters depending upon the environment and object reflectivity. There are two modes of design. In the first the sensor and detector pair is housed only on the front of the robot with one exactly in the front and the other two at approximately 60 degrees either sides to it. In the second design the three sensors are places all around the robot with each separated by 120 degrees to its neighboring pair. This layer can also be used to estimate the distance to which the obstacle is away for the robots. The second type of sensor layer houses infrared sensors. Five pairs of sensors and detectors are places equally spaced all around the robots. The IR emitters of all five pairs of sensors are enabled simultaneously through a logic-level FET, and are turned on by the control lines from the microcontroller. The detectors are designed such that the emitters are

driven at 38kHz modulated on 833Hz. The microcontroller can be programmed to produce the modulated wave. The detectors have built-in filters that single out the 38kHz/833Hz signal and provide a digital output to the microcontroller informing it if an object is present. Only binary decisions as to whether obstacles are present within a certain distance can be made.

The next layer is the control layer that houses the controller and the associated memory. The control layer has a Phillips 80C552 microcontroller with its associated memory. It has 16 bit address lines and 8 bit data lines that are time multiplexed on a 16-bit bus line. The layer also has the clock oscillator, which produces clock signals at an 11.33 MHz. The microcontroller has various analog to digital converters, PWM lines and input output ports. The final layer is the communication layer board. It houses an RF antenna and transceiver in addition to the other peripheral interface devices that the antenna system needs to support.

We have tried to use the groundscouts for our mine detection application. Each of the layers is given a specific task in the design for the mine detection application. The specifics that each layer would be dealing with in the application are given as follows. The motor-wheel base would be responsible for physical locomotion over the mine terrain. Trials were made to ensure the speed of the motors and the wheels with respect to specific terrains. The H-Bridge and power layers were given the usual role of

providing power distribution to the entire robot and directional data to the motors in the locomotive base.

The infrared layer was used to sense the mines over the minefield. The mines were programmed to emit infrared waves detectable by the receivers in the infrared layer. If IR ability were absent other sensory information (thermal scanning etc) pertaining to the materials of which mines are made could be used for detection. The signal that the mines would transmit was defined to be a 900 Hz square wave modulated over a 38 KHz carrier. The ultrasonic sensors are employed to detect obstacles and other passing robots. The ultrasonic sensors have the ability to estimate distance of any obstacles, which can obstruct the path of the robots. The control layer houses the microcontroller and the application program and the control of the various layers.

The robots were designed to forage for mines over a minefield. The obstacle avoidance and mine sensing routines run parallel to the foraging routines. When a robot is successful in detecting a mine it stops foraging and goes into a state of waiting until four of them are found at the location of the mine, which initiates demining. We have in our emulations assumed that four of the robots are required to successfully demine a mine. A pictorial description of four robots demining a mine is shown in Figure 23.

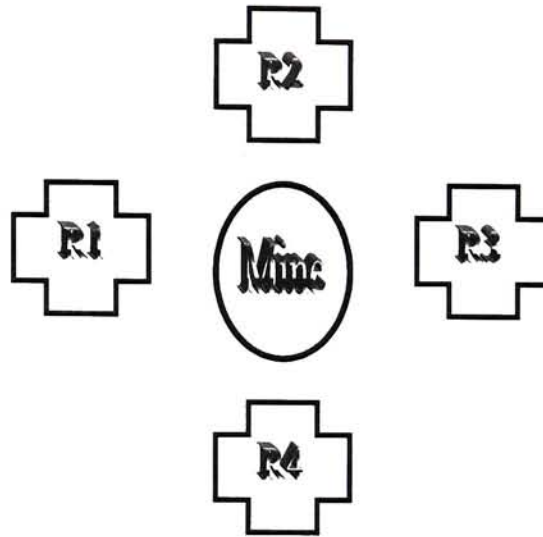


Figure 23. Collective action of four ants to demine a mine

Successful results were obtained both at the simulation level and the emulation level employing these robots for mine detection. Additional advantages could be made by utilizing the communication board for inter robot communication to make the system more effective. Intra robot communication data could be information containing mine locations, scent distributions and others that are aimed at improving the performance of the system, as a whole. Though the results were successful in demonstrating the ability of the robots executing the mine detection task, we had a variety of difficulties in bring up the system to works. Some of these problems speak for the complexity that poses when a decision is made to transform a simulation level algorithm to real time implementation. In essence the mine detection task is highly complex at practical levels and requires a high degree of precision and suave resources for implementation.

The first major problem that a practical scenario would be experiencing is that of how to evaluate the lifetime of the ants involved in the mine detection process. In our evaluation we equipped the robots with finite life batteries which are expected to power up the whole robot during the entire operation. However, could be a very fragile expectation, as we found in our analysis from the groundscouts that gradual weakening of the robots could cause the robots to come to an absolute halt abruptly. This could result in a temporary or permanent loss of the robot. A means that could monitor battery life and reflect its condition for adequate changes should be incorporated in the system. Not only was the danger of losing the robot's life, but some of the functionalities that the robot carry can be affected by battery weakening. When open loop operations are run in the system, loop parameters are not modified explicitly by feedback, in which case operations are performed based on environmental parameters. One such unpredictable environmental parameter is battery life. Software fixes can be made to rectify such errors, but it would instead have constraints on the sensory abilities of the robot. Thus it is very important to have a balance between complexity and robustness of the system.

Another important issue that erupted during the analysis was sensory and actuator issues. The groundscouts were very good in terms for actuator abilities, but were limited by the sensory abilities for a complex application like mine detection. The groundscouts were equipped with infrared sensors, proximity sensors and ultrasonic sensors. The demonstration uses the ultra sonic sensors to sense obstacles and distance, the infrared sensors and proximity sensors to detect the presence and absence of mines. The

ultrasonic sensors were positioned in the front of the robots one in the center and two others positioned at 45 degrees on either side to the one on the center. The basic problem with the ultrasonic sensors was the cone angle it had for both transmission and reception. Figure 24 shows how the cone angle would be affecting the detection of obstacles. Figure 24 shows how the ultrasonic sensors are able to capture the presence of obstacles. The angle AOB is the semi-cone angle of the transmitter of the ultrasonic. The semi cone angle is defined to be half of the angular range the spread of the ultrasonic transmitter. From the figure we can understand that the semi-cone angle can drastically affect the influence of the efficiency of the ultrasonic sensors. The shaded area SA as seen from Figure 24 is the area that the sensors would not be able to detect obstacles. The irony is that SA is very close to the sensor itself which means that the robot is bound to collide against anything within the shaded area SA.

Another important property of the ultrasonic sensors is that they will be able to perform detection when the obstacle is near flat and perpendicular to it, which may not be the case with most obstacles. The demonstration would contain other robots to be the obstacles which would not be flat surfaces so the reflected ray may scatter and perhaps would not be received by the receiver. This makes the obstacle detection process complex and prone to errors. However, software improvement of the ultrasonic sensors is done by a group of students to improve its capabilities. They were successful in performing the obstacle avoidance in their applications [32, 33]. Figure 25 shows a snap shot of the

experiments conducted by myself at Rochester Institute of Technology with the groundscouts.

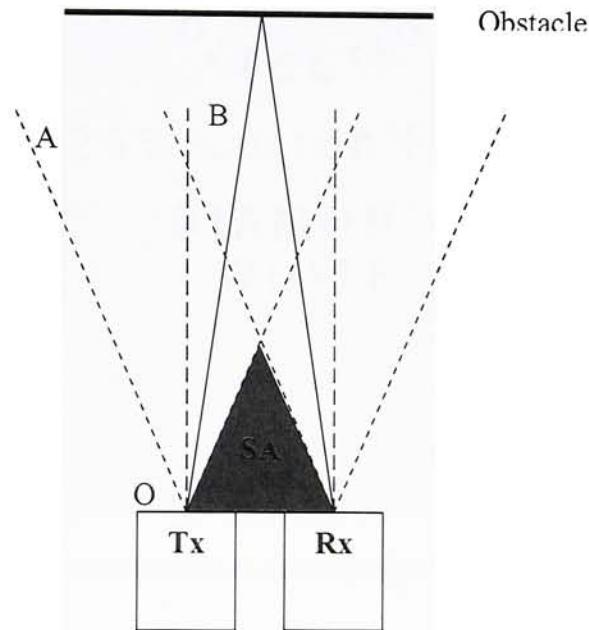


Figure 24 Ultrasonic Sensor and its sensory range

This is a first step in moving in towards practical realization of employing only robots for the mine detection process. The potential issues that could arise when such a step was to be taken have been logged and remedial measures to address them would be contemplated in future research.

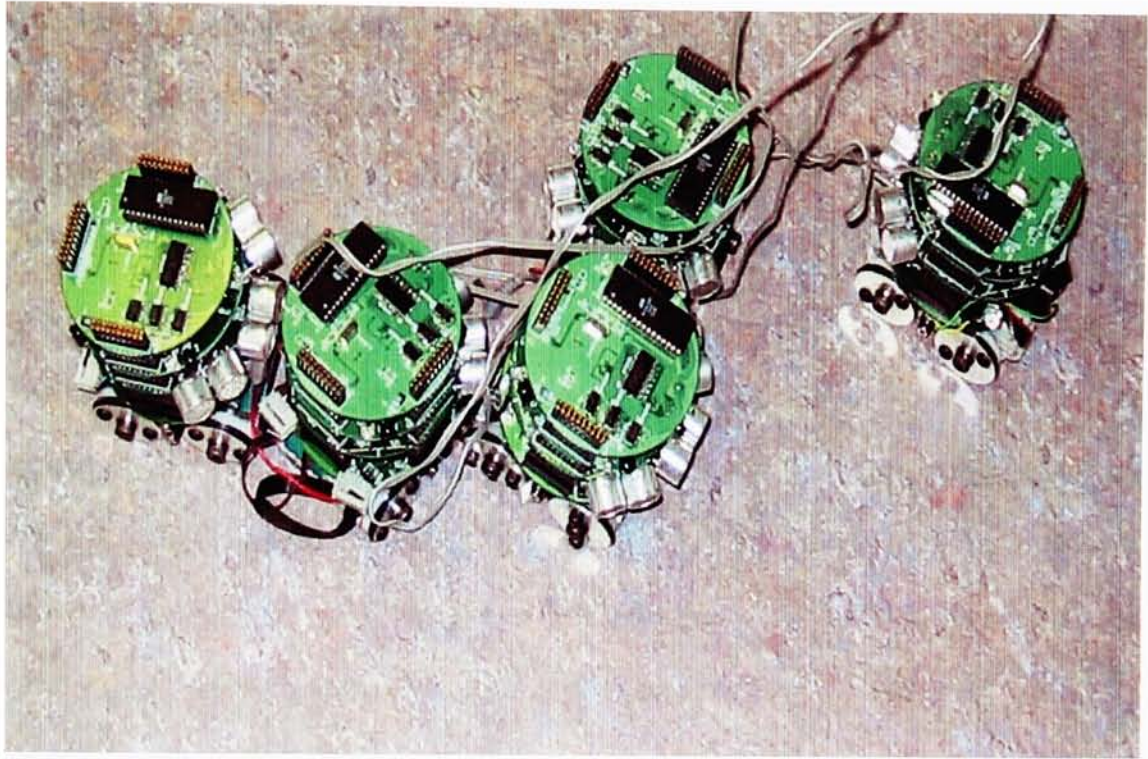


Figure 25. Groundscouts in the demonstration of Mine Detection

5.1 Results of the GroundScouts Experiment

The robots were made to operate on a level platform (the field) which was a square surface of dimension approximately 1.5 meters. A dummy mine was placed at various locations of the field that had the ability to spread IR rays. The IR rays were basically aimed at realization for direction vectors for the foraging robots to follow. The intensity of the radiation captured by the ultrasonic sensors was used to pick up distance information from the mine. The program was tuned to capture various ultrasonic reading corresponding to distances of 0.25, 0.5, 0.75 meters to initiate the behavioral transition

from foraging to trail following. As expected the more the scent distributed purview (in our case the software initiation by the ultrasonic sensors trigger) the better the convergence in terms of time required for detection. We used four robots detecting one mine for most of our experimental observations. Runs were averaged over five observations for observation results. We should mention that some of these runs failed to converge due to robot accidental collisions, power irregularity stoppage and collisions against the boundaries (a wall surrounding the field about a foot high). A burned chip on the power layer caused the power irregularity. The chip was responsible to convert battery voltage to 5V DC using a switch regulator. It has been fixed after the experiments were performed. The average time required for the simulations were in the range of one to three minutes.

6. Future work

There are certain areas where the present work could be improved on. The time required completing the detection of the mines in the region can be reduced if the ants use the information of the mines that it has detected in deciding on the future foraging strategy. Improved results can be obtained if the ants adaptively change their map (the division of the foraging region into distinguishable regions) of the foraging area in accordance with the updated mine distribution. A cost function approach can also be utilized for such a set up. By updated mine distribution we mean the distribution that an ant would have after it has defused a mine at a particular point, in comparison to the initial mine distribution that it had assumed. Also the algorithm could be applied to scenarios where the mines can be mobile. Simulations can be performed in situations where the nature of the mines can be different and demand a defusing technique different from the rest of the mines. The groundscouts can be improved in functionality to demonstrate the realization of the mine detection task better. For example, communication protocols and GPRS routines would enhance the functionalities and realization of the robots.

7. Conclusions

The problem of mine detection still is solved using very traditional techniques. The deployment of robots for the purpose of mine detection is indeed new and needed a lot of confidence built-up for practical implementations. In our approach, the use of swarm intelligence helps in creating a confidence. Our simulation results show that in almost all cases the convergence is well assured. There can be situations where the ratio of the number of mines to ants deployed is low. In that case all the ants may end up at the mines and wait for the others to arrive. Such a situation is called *freezing*. Freezing, although unlikely, can be an observable feature. We in our simulations found that on average freezing is expected to occur when the mines-to-ants ratio is approximately equal to 1 or less. Real time emulations of the swarm intelligence based algorithm on ground scouts take the performance of it closer to practical implementations.

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